# The Short-run Effects of Opening Mobile In-App Payment Systems: Evidence from South Korea*

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**Abstract**

Mobile app platforms are highly concentrated – Apple and Google each distribute over 75% of the total number of apps installed on the relevant devices. These platforms generally require developers to use a built-in system for processing payments at a tax rate of 30% for both the initial purchase of an app and any subsequent in-app purchases. In September 2021, South Korea became the first country to ban this lock-in; purchases made in the country may be conducted through any billing system developers wish. We analyze the impact of this policy change on demand for apps and revenue using difference-in-differences techniques and data from a leading app analytics firm from January 2018 to February 2022. We find limited suggestive evidence that the policy change may have decreased app installation rates.

*JEL Codes*: K21; L12; L22; L41; L89

*Keywords*: Platform, In-app Billing System, Tying, Taxation, Industrial Organization

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# 1 Introduction

Many digital platform markets are highly concentrated, dominated by a few players who have built a large share through network externalities (Rochet and Tirole 2003). These players often employ 'tying' strategies to extend their dominance in one market to other markets (Carlton and Waldman 2002). By foreclosing rivals, tying can lead to the monopolization of the market for the tied good (Whinston 1990). For example, Microsoft once tied its Internet Explorer browser with its Windows operating system to hamper the growth of competing browsers. The lack of competition from the exclusionary conduct associated with tying raises several anti-competitive concerns. The price of tied products is likely to be above the competitive equilibrium price and the level of product variety is likely to fall, both of which contribute to a decrease in consumer welfare (Whinston 1990). It can also negatively affect the level of innovation in the tied good market as potential entrants choose not to invest, which in turn further strengthens an incumbent's dominant market position (Choi and Stefanadis 2001).

Our study focuses on the market for mobile apps, which features substantial tying. Google and Apple, the leading firms in the market for mobile operating systems, each operate a distribution platform (Google Play Store and Apple App Store) that has near-monopoly power over the sale and distribution of apps to the relevant end-users. These firms have used the power implicit in their access to a large base of mobile users to dictate contract terms to app developers. Among these terms is a requirement to exclusively use the platform's payment system to process in-app purchases. On both platforms, 30% of every purchase is remitted to the platform owner as a commission.

These contracts have been subject to public and legislative scrutiny in many countries in recent years as developers of large and popular apps have complained that the current system is unfair and limits development effort (see, e.g. Allyn 2021). The most successful effort, from the perspective of app developers, is a 2021 South Korea law that banned app store operators from enforcing exclusivity requirements for in-app payment processing.

We study the effects of the law and subsequent responses from platform owners on app distribution. The law came into effect on September 14, 2021. On December 18, 2021, Google responded to the law by adjusting its platform policies for apps that serve users in South Korea. Developers of

Play-distributed apps may offer such users an in-app billing system that differs from Play's built-in billing system if they complete required forms and agree on additional terms. Apple has not changed its policy until June 30, 2022 (about six months after Google has changed its policy)[12]. Our prior is based on the claims of app developers: as the commission payment acts as a tax, developers no longer subjected to the tax (or subjected to a lower tax) may be able to improve the quality of their apps, thus increasing the number of users with the apps installed and increasing the income of developers from in-app purchases. In fact, app developers have incentives to diverge away from their existing use of the platform's proprietary in-app payment processing if enough government protection is insured and significant other developers are shifting away from it (Hwang and Kim 2022).

We test these hypotheses using app-level panel data on installs and revenue from Appfigures, a market research firm. We define Play-distributed apps on mobile devices located in South Korea as the treated group and the date of Google's policy change as the date of treatment. We compare outcomes for apps in this group against outcomes in three sets of potential control groups. First, we consider Play-distributed apps in countries with closed billing systems (i.e. those that are not South Korea). Second, we consider apps distributed by Apple's App Store. Third, we consider Play-distributed apps in South Korea during the pre-treatment period.

We test for changes in app-level outcomes using difference-in-differences and triple difference-in-differences techniques. While our point estimates suggest that installs decreased and revenues increased post-reform, these effects are imprecisely estimated. We therefore interpret these findings as a null result. In other words, we estimate that the law did not have an identifiable effect on these outcomes in the period immediately after the law was implemented.

Our work contributes to the broader literature exploring the theoretical and empirical implications of tying strategies. Within this literature, most of the work has focused on examining the effects of tying (Carlton and Waldman 2002; Amelio and Jullien 2012; Derdenger 2014; Choi and Jeon 2021). In contrast, studies that analyze the effects of attempted remedies and/or regulations that seek to unbundle once-tied products are relatively scarce.

1. (**applewebsite**) https://developer.apple.com/support/storekit-external-entitlement-kr
2. Alike Google, Apple still charges a 26% commission rate to app developers using a third payment option for in-app transactions

The structure of this paper is as follows: Section 2 provides a brief background on the app market and existing platform polices on in-app billing systems. Section 3 illustrates data and descriptive evidence; Section 4 introduces identification strategy to estimate the changes in the outcome variables of interest and provide implications about the empirical results. Finally, Section 5 concludes with some remarks of improvements and a discussion of possible future research.

# 2 Background

## 2.1 App Stores

App stores are digital platforms for selling and distributing mobile applications (apps). Developers publish their apps on these platforms while consumers use the platforms to discover, purchase, and access apps. Developers earn revenue through three methods. First, developers may charge an up-front price to download the app. Second, developers may embed advertisements into the app. Third, developers may lock certain features behind in-app purchases. These methods may be combined. For example, a strategy game app may be offered to download for free, but come with advertisements displayed between each round or before each turn. Users may pay a fee to remove such advertisements. The app may offer additional features in exchange for fees such as in-game performance bonuses (e.g. increases to the rate at which the user progresses through the game) or changes to the appearance of game features (e.g. 'cosmetic' changes to the characters in the game that do not affect game outcomes).

App stores offer users (among other features) limited security guarantees, a centralized record of purchases, and convenient re-installation of apps on new devices (e.g. a user changing mobile devices which both use the Google Play Store may reinstall their applications with minimal intervention). These platforms offer developers exclusive access to large user bases (i.e. developers who wish to offer their apps to Android users must do so through the Google Play Store) and baseline functionality related to online communication, payment systems, and cloud-based storage (of e.g. saved documents or play sessions). App stores generate revenue primarily by charging a commission on both purchases of apps with up-front prices and in-app purchases.[3] Historically, the 'tax rate' charged by both Google and Apple has been set at 30%. In other words, when a user spent \$10 on

3. Google also offers a monthly subscription service that includes access to a rotating library of paid apps.

either an up-front or in-app purchase, the developer received \$7 and the platform received \$3. In early 2021, both Apple and Google reduced the tax rate to 15% for the first \$1 million of revenue earned by a developer each year.

Other app stores exist. For example, three major South Korean telecommunications companies maintain the One Store platform which is installed on all mobile devices sold in South Korea that are serviced by the relevant wireless networks. One Store offers developers a lower commission rate of 20% when using the One Store payment platform and a 5% service fee when using other platforms.

### 2.2 The South Korean Law and Responses

Responding to antitrust concerns, the South Korean National Assembly banned the operators of app store platforms from imposing payment methods on app developers starting September 14, 2021. This policy change made South Korea the first country to compel the opening of in-app billing systems by law.

The law required platform operators to submit detailed plans about how they would change their policies to comply. Google implemented changes in December 2021 that allowed developers to offer users in South Korea an alternative in-app billing system. To do so, developers must certify compliance with industry standards for security and fraud prevention, report all transactions from users in South Korea on a monthly basis, and pay a per-transaction service charge equal to the non-South-Korea market rate minus 4%. In other words, while developers may offer users an alternative payment system, most payments are still taxed at 26%. While Apple has indicated an intent to cooperate with the law, it was not until June 2022 that it has announced changes to its Terms of Service to comply and allowed developers to use third-party payment systems.

Regulators in other countries are considering similar actions. The Netherlands' antitrust authority has ordered Apple to allow alternative payment methods for dating apps. In the United States, the Open App Markets Act is a bipartisan effort to untie payments and implement additional restrictions on app platform providers; the legislation was drafted in part in response to a lawsuit from a prominent app developer challenging Apple's in-app payment restrictions.

## 3 Data and Descriptive Evidence

To study the short-run effect of South Korea's legislation and Google's policy response, we obtain panel data on app downloads and revenues from Appfigures. Appfigures is a firm that provides developers tracking and analytics services. Specifically, we obtain Appfigures' 'Public API' dataset of installations and revenue for nine apps offered in five countries at the daily level from January 2018 to February 2022.[4] We aggregate these to the app-country-week level. We define the pre-reform period as January 2018 to November 2021 and the post-reform period from December 2021 to February 2022. It is important to note up front that these data consist of Appfigures' estimates of the relevant metrics. Appfigures forms these estimates by training prediction models on private data reported by developers who opt-in to its data collection program.[5] We proceed under the assumption that the Appfigures data are noisy measures of the true install and revenue data that have neutral bias relative to the reform. By 'neutral bias' we mean that to the extent that the Appfigures estimates are biased measures of the true data, that bias is not affected by the reform. Thus, comparisons of app performance pre- and post-reform can identify at least the direction of any effects, if not the magnitudes.

The apps we consider are the top-grossing game apps distributed on Google's Play Store that were listed in both the United States and Korea as of November 2021.[6] We collect data on the performance of these apps in these countries and additionally in Japan, Germany, and France. We chose these countries as countries in which per-capita spending on mobile apps is similar to that in South Korea. According to Statista, through the first three quarters of 2021, Japan had the highest mobile spending per capita with $149 US. South Korea was second with $95 US, followed by the United States with $90 US. Germany and France were 7th and 8th, respectively.

Table 1 enumerates the apps, their developer, and their rank in the Google Play Store in both South Korea and the United States in November 2021. Table 2 reports summary statistics on

4. The next most popular game across both the United States and Korea in November 2021 was Blue Archive, which was released in those market that month. As no pre-reform data is available for this app, we remove it from consideration.

5. In other words, Appfigures observes publicly-available data from Google and Apple for all apps, and private data from developers that opt-in. Appfigures trains prediction models on the set of apps for which private data are available, and produces estimates of the private data for all apps. It is these estimates that we use as the outcome measures in our analysis.

6. Some of the top-grossing game apps in South Korea are not available in other markets.

**Table 1: App rankings**

| App | Developer | Rank KR | Rank US |
|---|---|---|---|
| Genshin Impact | COGNOSPHERE PTE. LTD. | 6 | 6 |
| Cookie Run: Kingdom | Devsisters Corporation | 12 | 57 |
| Roblox | Roblox Corporation | 13 | 7 |
| Brawl Stars | Supercell | 15 | 87 |
| Empires and Puzzles | Small Giant Games | 16 | 10 |
| Epic Seven | Smilegate Megaport | 20 | 48 |
| MARVEL Future Fight | Netmarble | 23 | 68 |
| Lords Mobile: Tower Defense | IGG.COM | 44 | 45 |
| Candy Crush Saga | King | 60 | 2 |

*Notes:* The table above shows names and developer names of each app in the sample and their respective rankings in South Korea as well as their rankings in the U.S. as of November 2021. The full name of the app 'Empires and Puzzles' is 'Empires & Puzzles: Match-3 RPG'.

installs and revenue both pre- and post-reform in Korea and other countries. Focusing on the performance of apps in South Korea market, download rates for 7 of the 9 apps decreased post-reform, though revenue increased for 6 of the 9 apps. Similar trends occurred in the other countries we study, though they are generally less pronounced than in South Korea. For example, while the monthly new install rate for Genshin Impact decreased by an average of 46% in Korea in the post-reform period compared to the pre-reform period, the Genshin Impact install rate decreased by an average of only 28% in other countries. At the same time, Genshin Impact's monthly revenue increased by 27% in South Korea but increased by only 6% in other countries.

We also examine the performance of apps on the Apple App Store for those apps in our data which are multi-homed between both stores (Bresnahan, Orsini, and Yin 2015). Although the South Korean policy change applied in theory to both stores, the fact that Apple has not yet implemented changes to comply with South Korea's rules allows us to use the performance of these apps on the Apple App Store performance as a potential control. Table 3 reports summary statistics for the performance of the relevant four apps on the Apple App Store. The pattern of decreased level of new installs post-reform remained the same for the apps on the Apple Store in South Korea. Unlike the upward revenue trend observed for these apps on the Play platform post-reform, App Store revenues for these apps broadly decreased post-reform.

Table 2: **New Installs and Revenue for Apps on Google Play Store**

| | Korea | | Others | | Change | |
|---|---|---|---|---|---|---|
| | Pre-Law | Post-Law | Pre-Law | Post-Law | Korea | Others |
| *New Installs (000s / month)* | | | | | | |
| Blue Archive | 64.38 | 7.38 | 8.31 | 1.17 | -0.89 | -0.86 |
| Cookie Run: Kingdom | 58.06 | 16.97 | 9.05 | 5.54 | -0.71 | -0.39 |
| Brawl Stars | 53.13 | 14.43 | 32.41 | 16.96 | -0.73 | -0.48 |
| Roblox | 24.19 | 26.48 | 55.09 | 55.58 | 0.09 | 0.01 |
| Genshin Impact | 21.22 | 11.54 | 22.84 | 16.96 | -0.46 | -0.26 |
| Candy Crush Saga | 16.83 | 13.53 | 35.61 | 33.44 | -0.2 | -0.06 |
| Empires and Puzzles | 11.85 | 2.05 | 9.98 | 2.54 | -0.83 | -0.75 |
| MARVEL Future Fight | 9.18 | 4.05 | 4.12 | 6.00 | -0.56 | 0.46 |
| Lords Mobile: Tower Defense | 8.81 | 14.19 | 16.24 | 17.87 | 0.61 | 0.1 |
| Epic Seven | 7.99 | 2.90 | 4.03 | 1.48 | -0.64 | -0.63 |
| *Revenue ($000s / month)* | | | | | | |
| Cookie Run: Kingdom | 854.79 | 255.29 | 67.84 | 83.99 | -0.7 | 0.24 |
| Blue Archive | 608.06 | 194.06 | 122.55 | 44.48 | -0.68 | -0.64 |
| Brawl Stars | 242.56 | 197.90 | 195.72 | 175.90 | -0.18 | -0.1 |
| Epic Seven | 239.99 | 240.96 | 193.50 | 151.19 | 0 | -0.22 |
| Genshin Impact | 212.64 | 271.23 | 760.06 | 804.35 | 0.28 | 0.06 |
| Empires and Puzzles | 136.92 | 141.89 | 355.77 | 384.70 | 0.04 | 0.08 |
| MARVEL Future Fight | 115.32 | 69.71 | 60.39 | 39.18 | -0.4 | -0.35 |
| Lords Mobile: Tower Defense | 99.91 | 120.50 | 460.94 | 405.98 | 0.21 | -0.12 |
| Roblox | 68.06 | 310.33 | 426.84 | 912.83 | 3.56 | 1.14 |
| Candy Crush Saga | 41.53 | 74.84 | 844.57 | 1336.50 | 0.8 | 0.58 |

*Notes:* The reported statistics are monthly averages. 'Revenue' is the net revenue (post-commission). 'Pre-Law' is the period between January 2018 to November 2021 while 'Post-Law' is the period between December 2021 and February 2022. 'Others' denotes the average over Japan, US, France and Germany.

Figure 1 and Figure 2 depict these data for each app. Figure 1 illustrates the logged number of new installs in each week for each app in Korea, while Figure 2 illustrates the logged revenue. For each app and outcome, the black solid line represents the period potentially affected by the policy change: June 2021 through February 2022. This period consists of the three months prior to the implementation of the law to two months after Google changed its Terms of Service to allow alternative in-app payment systems. The black dot marks the starting point of the observations, as not all apps were released at the start of our observation period. Two vertical lines represent September 14, 2021, and December 18, 2021, which stand for the time when the legislation became effective and the time when Google's policy changes went into effect, respectively.

**Table 3: New Installs and Revenue for Apps on Apple App Store**

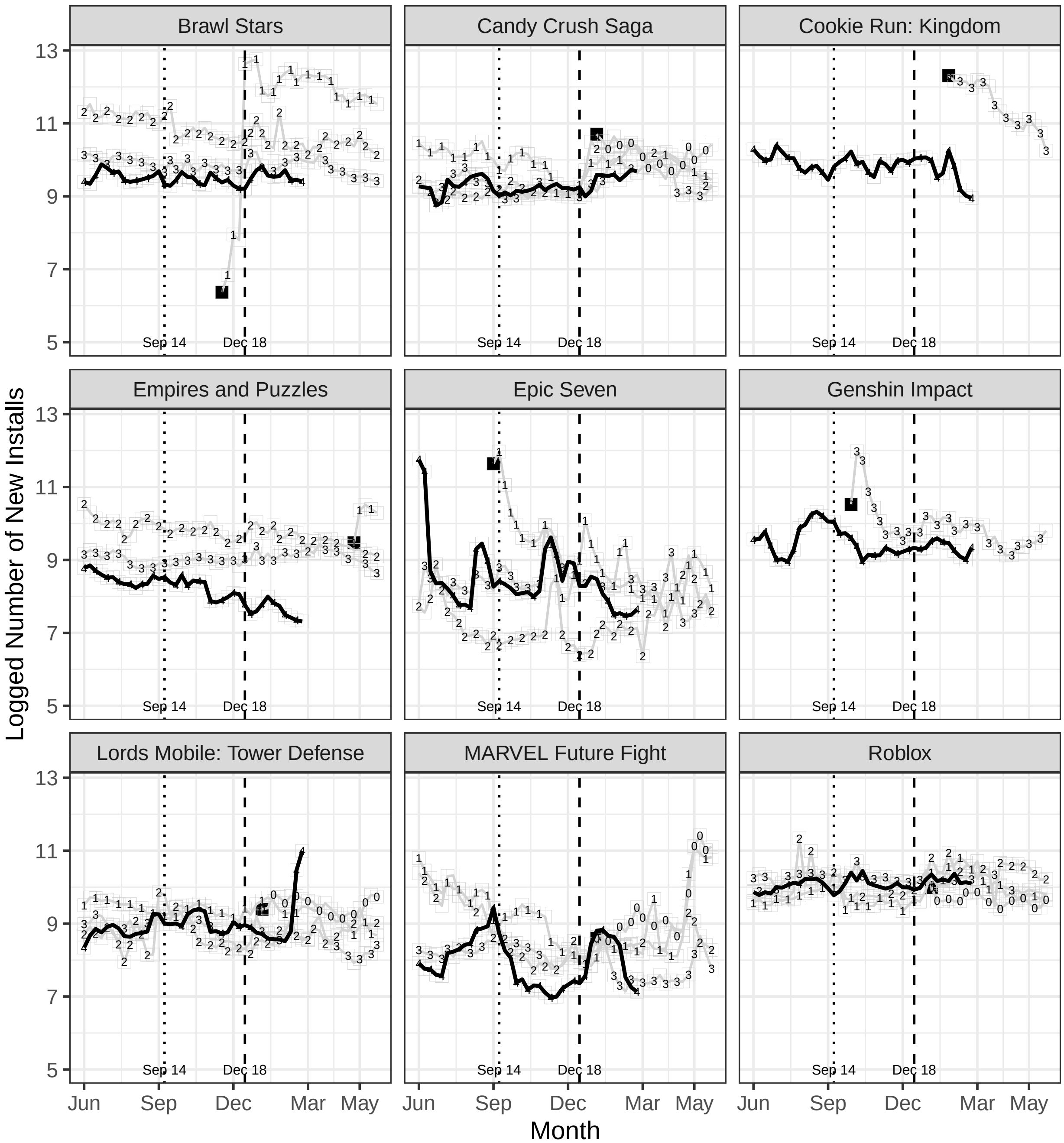
| | Korea | | Others | | Change | |
|---|---|---|---|---|---|---|
| | Pre-Law | Post-Law | Pre-Law | Post-Law | Korea | Others |
| *New Installs (000s / month)* | | | | | | |
| Cookie Run: Kingdom | 24.37 | 7.05 | 14.28 | 8.13 | -0.71 | -0.43 |
| Genshin Impact | 6.73 | 5.91 | 30.19 | 26.21 | -0.12 | -0.13 |
| Roblox | 6.46 | 14.39 | 57.03 | 84.46 | 1.23 | 0.48 |
| Lords Mobile: Tower Defense | 1.77 | 1.05 | 10.82 | 8.22 | -0.41 | -0.24 |
| *Revenue ($000s / month)* | | | | | | |
| Cookie Run: Kingdom | 405.29 | 166.71 | 147.95 | 207.04 | -0.59 | 0.4 |
| Genshin Impact | 167.35 | 143.97 | 735.45 | 826.56 | -0.14 | 0.12 |
| Lords Mobile: Tower Defense | 33.09 | 11.06 | 265.20 | 320.27 | -0.67 | 0.21 |
| Roblox | 9.19 | 33.79 | 865.59 | 3694.64 | 2.68 | 3.27 |

*Notes:* The reported statistics are monthly averages. 'Revenue' is the net revenue (post-commission). 'Pre-Law' is the period between January 2018 to November 2021 while 'Post-Law' is the period between December 2021 and February 2022. 'Others' denotes the average over Japan, US, France and Germany.

Five apps appear to exhibit lower level of logged downloads during the affected period while the other four apps appear to have similar level of logged downloads. This means that the effect of treatment on logged downloads is likely to be either negative or marginal. The pattern looks similar for the trend of revenue estimates of these apps except that about half the apps show higher revenue estimates during the affected period. This means that the effect of treatment on logged revenue is likely to be either positive or marginal.

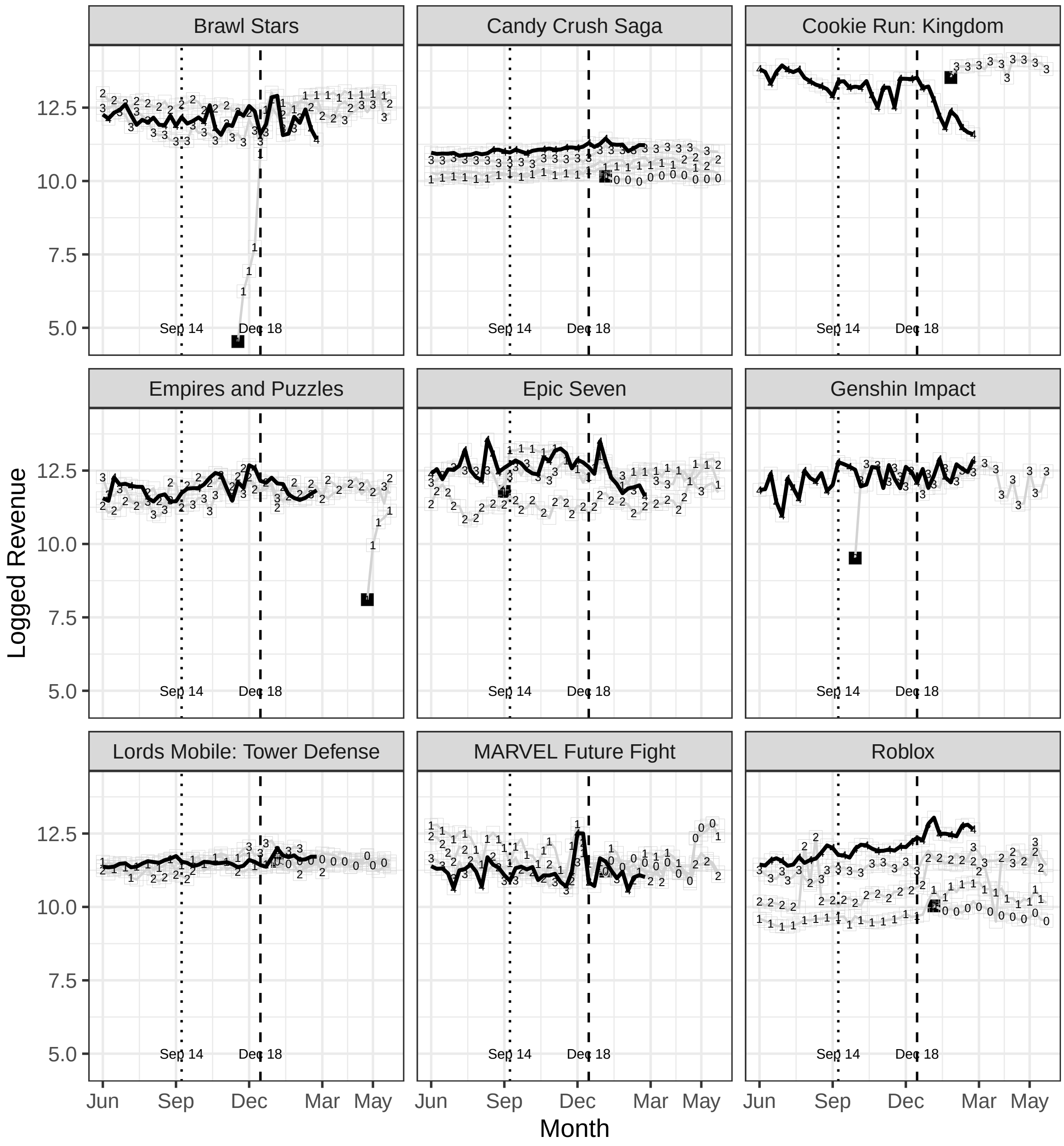
The analogous data for App-Store-distributed apps are illustrated in Figures 3 and 4. While Roblox experienced steady increases in installs and revenue from 2018 to 2021, these increases tapered off in the post-reform period. On the other hand, Lords Mobile: Tower Defense suffered decreased performance from 2018 to 2021, but experienced a significant increase in installs post-reform, though not in revenue. The other two apps show a downward trend or minimal changes, yet it is hard to conclude it as a result of the policy or of unknowns that are irrelevant to the policy, as their data are relatively short in time.

**Figure 1: New installs of apps on Google Play in Korea**



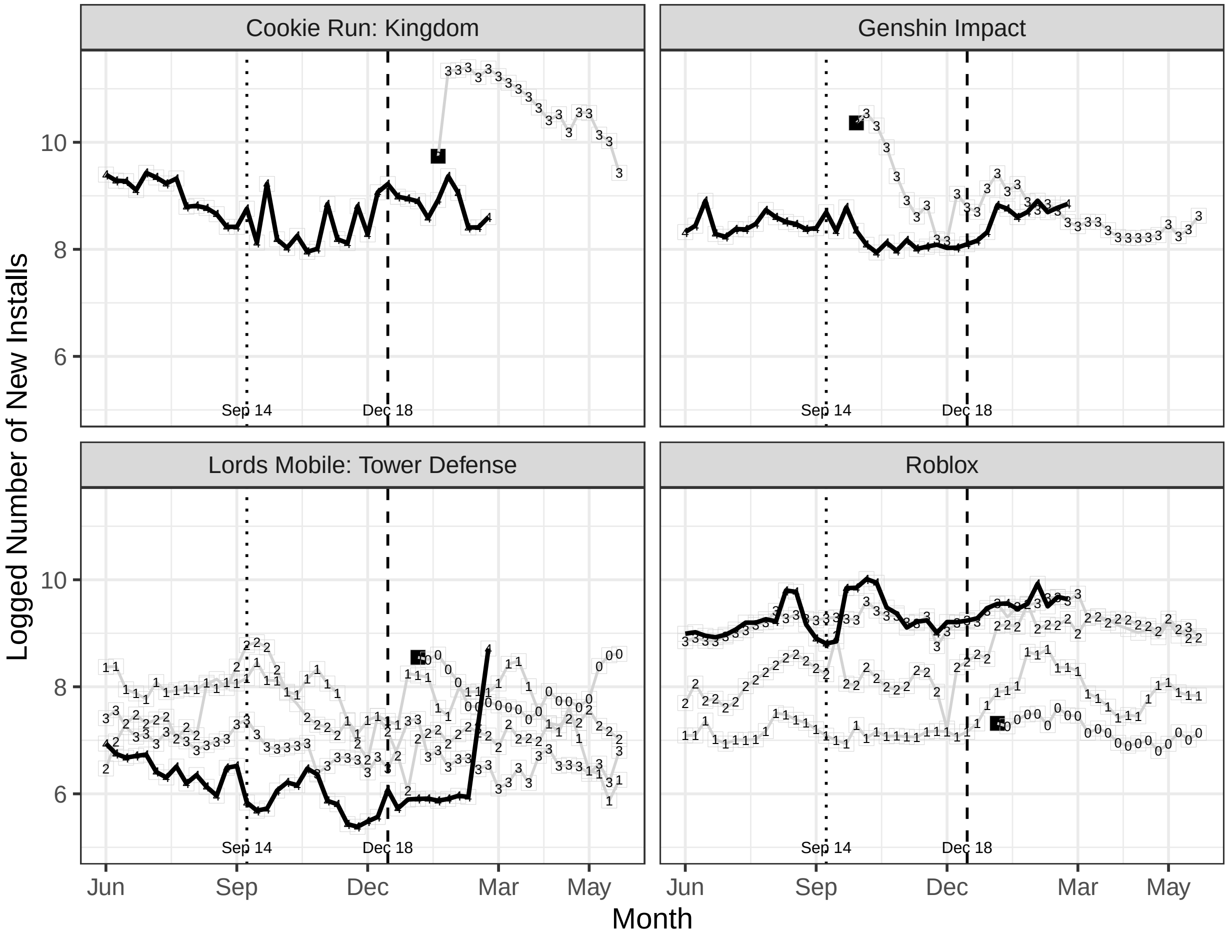

*Notes:* These figures illustrate the time trend of new installs across different periods denoted by numbers from 0 to 4. The most recent period is period 4, illustrated with a solid line, which consists of the three months prior to when the law became effective until the most recent data. The other periods represent annual lags, so period 3 consists of June 2020 - May 2021, period 2 consists of June 2019 - May 2020, period 1 consists of June 2018 - May 2019, and period 0 consists of January 2018 - May 2018. A black square marks the entry of each app.

**Figure 2: Estimated revenue for apps on Google Play in Korea**




*Notes:* These figures illustrate the time trend of estimated revenues across different periods denoted by numbers from 0 to 4. The most recent period is period 4, illustrated with a solid line, which consists of the three months prior to when the law became effective until the most recent data. The other periods represent annual lags, so period 3 consists of June 2020 - May 2021, period 2 consists of June 2019 - May 2020, period 1 consists of June 2018 - May 2019, and period 0 consists of January 2018 - May 2018. A black square marks the entry of each app.

**Figure 3: New installs of apps on Apple App Store in Korea**




*Notes:* These figures illustrate the time trend of new installs across different periods denoted by numbers from 0 to 4. The most recent period is period 4, illustrated with a solid line, which consists of the three months prior to when the law became effective until the most recent data. The other periods represent annual lags, so period 3 consists of June 2020 - May 2021, period 2 consists of June 2019 - May 2020, period 1 consists of June 2018 - May 2019, and period 0 consists of January 2018 - May 2018. A black square marks the entry of each app.

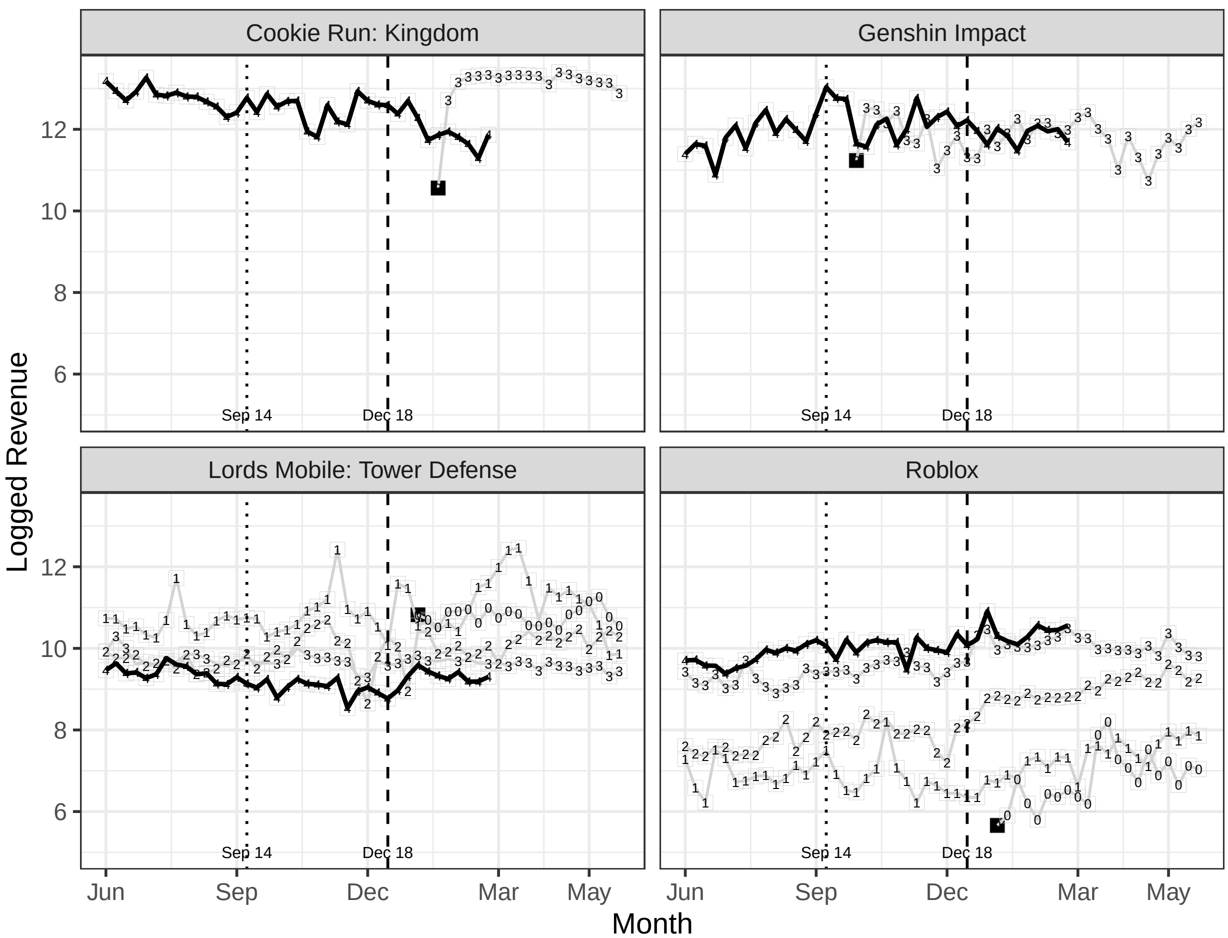
# 4 Identification and Estimation

## 4.1 Motivational Framework

To motivate our empirical work, we consider a model in which a developer seeks to maximize the profit they earn from an app. In the model, the price of an in-app item determines the volume of in-app transactions, and a consumer's decision to install the app depends on the app's quality and in-app prices.

Let $p$ be price of an in-app item and $w$ be app quality. Let $q(p)$ be the quantity of in-app

**Figure 4: Estimated revenue for apps on Apple App Store in Korea**




*Notes:* These figures illustrate the time trend of estimated revenues across different periods denoted by numbers from 0 to 4. The most recent period is period 4, illustrated with a solid line, which consists of the three months prior to when the law became effective until the most recent data. The other periods represent annual lags, so period 3 consists of June 2020 - May 2021, period 2 consists of June 2019 - May 2020, period 1 consists of June 2018 - May 2019, and period 0 consists of January 2018 - May 2018. A black square marks the entry of each app.

purchases per consumer as a function of the in-app price and $d(p, w)$ be the number of app installs, assumed to be decreasing in $p$ and increasing in $w$. Let $c(w)$ be the cost of developing the app, assumed to be increasing and convex in $w$. Finally, let $\tau$ be the commission (or tax) rate assessed on in-app purchases, assumed to be exogenous from the perspective of the developer. The developer chooses a price and quality that solves

$$\max_{p,w} \pi(p, w) = pq(p)d(p, w)(1 - \tau) - c(w). \tag{1}$$

Suppose that $\pi(p, w)$ is globally concave and there is an interior global maximum. The first order conditions for maximization are

$$\{w^*\} : \ \frac{\partial \pi}{\partial w} = 0 \Longrightarrow \ pq(p)(1-\tau)\frac{\partial d(w,p)}{\partial w} = \frac{\partial c(w)}{\partial w} \tag{2}$$

$$\begin{aligned} &\{p^*\} : \ \frac{\partial \pi}{\partial p} = 0 \Longrightarrow \\ &(1-\tau)(q(p)d(p,w) + p\frac{\partial q(p)}{\partial p}d(p,w) + pq(p)\frac{\partial d(p,w)}{\partial p}) = 0 \end{aligned} \tag{3}$$

By combining these expressions and rearranging terms, we can write an expression for the optimal price,

$$p^* = \frac{-q(p)d(p,w)}{\frac{\partial q(p)}{\partial p}d(p,w) + \frac{\partial d(p,w)}{\partial p}q(p)} \quad = \frac{\frac{\partial c(w)}{\partial w}}{q(p)(1-\tau)\frac{\partial d(w,p)}{\partial w}}.$$

Suppose that the cost function is convex in app quality, i.e., $c(w) = w^2$. From (2), we can write an expression for the optimal quality,

$$w^* = -\frac{1}{2}pq(p)(1-\tau)\frac{\partial d(p,w)}{\partial w}.$$

It can be shown that $\frac{\partial p^*}{\partial \tau}$ is calculated to be positive, meaning that as the commission rate drops, the in-app price decreases.[7] It can be also be shown that $\frac{\partial w}{\partial \tau}$ to be negative, assuming that app quality improvement attracts higher number of app downloads. Intuitively, in the absence of a quality characteristic to the product, changes in the commission rate would simply be passed through to consumers. However, the quality dimension acts as a additional wedge on which the

7. To see this, define $A \equiv q(p)(1-\tau)\frac{\partial d(w,p)}{\partial w}$. Then

$$\begin{aligned} \frac{\partial p^*}{\partial \tau} &= \partial \left( \frac{\partial c(w)}{\partial w} \left( q(p)(1-\tau)\frac{\partial d(w,p)}{\partial w} \right)^{-1} \right) / \partial \tau \\ &= \partial \left( \frac{\partial c(w)}{\partial w} A^{-1} \right) / \partial \tau. \end{aligned}$$

For the sake of simplicity in notation, write $c(w) = c$, $q(p) = q$, and $d(p,w) = d$. Then

$$\begin{aligned} &= \frac{\partial c}{\partial w} A^{-1} \left( \frac{\partial w}{\partial \tau} \left( 1 - A^{-1} q(1-\tau) \frac{\partial d}{\partial w} \right) + A^{-1} \frac{\partial d}{\partial w} q \right) \\ &= \frac{\partial c}{\partial w} A^{-1} \left( \frac{\partial w}{\partial \tau} (1 - A^{-1}A) + A^{-1} \frac{\partial d}{\partial w} q \right) \\ &= \frac{\partial c}{\partial w} A^{-2} \frac{\partial d}{\partial w} q > 0 \ \blacksquare \end{aligned}$$

commission rate acts: when the firm faces a commission rate, it does not receive payment for the 'full' quality of the app it has produced and therefore it reduces the quality of app while increasing the price.

We then examine how profit, the number of app downloads, and app quality respond with respect to change in commission rate ($\frac{\partial \pi}{\partial \tau}$, $\frac{\partial d(p,w)}{\partial \tau}$, $\frac{\partial w}{\partial \tau}$).

App profit responds negatively as the commission rate increases, since $\frac{\partial \pi}{\partial \tau} = -pq(p)d(w,p)$ is negative. Also assuming downward slope of an in-app item demand curve ($\frac{\partial d(p,w)}{\partial p} < 0$), $\frac{\partial d(w,p)}{\partial \tau}$ which by the chain rule becomes $\frac{\partial d}{\partial p}\frac{\partial p}{\partial \tau} + \frac{\partial d}{\partial w}\frac{\partial w}{\partial \tau}$ is implied to be negative. Therefore, developers are likely to gain more profit and the number of app downloads is likely to increase with lower commission rate.

## 4.2 Econometric Model

Our framework suggests that a drop in the commission rate should lead to an increase in profits (which we measure with revenues) and downloads. We estimate the effect of the policy change using a two-way fixed effects difference-in-differences (TWFE DiD) that compares the difference in outcomes for the treated group between the pre-treatment and post-treated periods to the difference in outcomes for the control group between the same periods. We estimate the parameters of

$$\log(Y_{ipct}) = \beta_0 + \beta_1 D_{ipct} + \alpha_i + \delta_p + \zeta_c + \gamma_t + u_{ipct}, \tag{4}$$

where $\log(Y_{ipct})$ is the logged outcome variable (either app installs or app revenue) for app $i$ distributed via platform $p$ in country $c$, at time $t$, $D_{ipct}$ is a treatment dummy that interacts $\text{PostReform}_t$, an indicator variable which is equal to 1 if $t$ is December 2021 or later, and $\text{Treat}_{ipct}$, an indicator variable which is equal to 1 if app $i$ distributed through platform $p$ for the users in country $c$ is in the treated group. Fixed effects for cross sectional units are represented by $\alpha_i$, $\delta_p$, $\zeta_c$, which are app-level, platform-level, country-level fixed effects, respectively. $\gamma_t$ represents time fixed effects, and $u_{ipct}$ represents idiosyncratic app-platform-country-time disturbances.

The treatment we are interested in is the opening of in-app billing systems and the corresponding decrease in the commission rate paid by firms. This treatment applies only to apps that are distributed by Google Play and installed on mobile devices located in South Korea. This implies there are three sources of variation available in the data: (1) different treatment status across sampled countries (Korea vs. Countries other than Korea), (2) different treatment status across the two app distribution platforms in Korea (Google Play Store vs. Apple App Store), and (3) different treatment status across different "years"[8] (Treated "year" vs. Control "year").

We consider three sets of potential control groups that could serve as counterfactuals for the treated group based on these sources of variation. The first control group is Play-distributed apps in countries that have closed billing system. In other words, we compare the performance of Google Play apps in South Korea to the performance of the same apps in other countries.

The second control group consists of apps published on Apple's App Store as Google implemented a response to the policy in December 2021, before Apple's implemented a response. We can therefore compare the performance of Google Play apps in South Korea to the performance of the same apps on Apple's App Store, for those apps that multi-home on both platforms.

Finally, the third control group consists of apps on Google's Play Store a year prior to the law being implemented. The use of this control group may be particularly helpful in the presence of seasonal trends.

The parameter of interest is $\hat{\beta}_1$, which represents the causal effect of Google's changed policy on app installs and app revenue, provided that the identification assumption is satisfied. For difference-in-differences estimator to produce unbiased estimates, the parallel trend assumption must hold: the difference between the treated and the control remains constant throughout the analysis period in the absence of the treatment. Since dependent variable is logged, $\hat{\beta}_1$ estimate can be interpreted as the percent change for treated apps during post-treatment period. $\hat{\beta}_1$ isolates the change in app installs and app revenue that cannot be explained by what was observed as the difference between the treated and control group in the pre-treatment period. In the appendix, we explore the parallel trends assumption for our different control groups and conclude that the control group most likely to satisfy the assumption is the group of Play-distributed apps downloaded in other countries.

8. Here we redefined "year" to begin on June 1 of one calendar year and conclude on May 30 of the following calendar year so that the treated weeks since December 2021 throughout February 2022 belong to the same "year". This is to compare the three months post-treatment against the six month prior months.

That said, it is possible that any results stemming from that control group are driven by seasonal trends in download and in-app purchase behavior.[9] To account for this, we explore specifications using two sets of control groups in a triple-difference-style approach. That is, we estimate the parameters of

$$
\begin{aligned}
\log(Y_{ipct}) = \beta_0 &+ \beta_1 \text{Post}_t \times \text{TreatPlatform}_{ip} \times \text{TreatCountry}_{ic} \\
&+ \beta_2 \text{Post}_t \times \text{TreatPlatform}_{ip} + \beta_3 \text{Post}_t \times \text{TreatCountry}_{ic} \\
&+ \beta_4 \text{TreatPlatform}_{ip} \times \text{TreatCountry}_{ic} \\
&+ \alpha_i + \delta_p + \zeta_c + \gamma_t + v_{ipct},
\end{aligned}
\tag{5}
$$

where $\log(Y_{ipct})$ is the logged outcome variable (either app installs or app revenue) at time $t$for app $i$ that belongs in platform $p$ and country $c$, $\text{Post}_t$ is an indicator variable which is equal to 1 if $t$ is December 18, 2021 or later, $\text{TreatPlatform}_{ip}$ is an indicator variable which is equal to 1 if app $i$-group $p$-platform pair is in the treated group, and $\text{TreatCountry}_{ic}$ is an indicator variable which is equal to 1 if app $i$-group $c$-country pair is in the treated group. For example, suppose we have observations about four apps each of which are distributed through three platforms across five countries. Then $i \in \{1, 2, 3, 4\}$, $p \in \{1, 2, 3\}$, and $c \in \{1, 2, 3, 4, 5\}$. If only platform 1 is treated, $\text{TreatPlatform}_{ip}$ equals one for all four apps distributed through platform 1 and is zero otherwise. If only country 1 is treated, $\text{TreatCountry}_{ic}$ equals one for all 12 app-platform pairs and is zero otherwise. Fixed effects for cross sectional units are represented by $\alpha_i$, $\delta_p$, $\zeta_c$, time fixed effects are represented by $\gamma_t$, and idiosyncratic disturbances are represented by $v_{ipct}$.

9. We further devised app-level synthetic control to remove some degree of seasonality in the data. However, since the weights put on control countries do not vary across time, the synthetic control still did not capture enough seasonal and cyclical variations. Event study using synthetic control suggests a preliminary evidence of violating parallel trend assumption and thus, here we stick to using observations from all four control countries for the analysis.

# 5 Results

## 5.1 Using Play-distributed Apps in Countries with Closed Billing System as Control

Our first estimates of Equation (4) come from focusing on Play-distributed apps (thus removing variation that comes from different app distribution platforms) and exploiting different treatment status across country. In other words, we ask whether Play-distributed apps in Korea experienced different outcomes in revenue and/or install relative to Play-distributed apps in other countries during the post-treatment period. Our data for these estimates includes observations of nine Play-distributed apps in five countries.

Table 4 summarizes the estimates of $\beta_1$. The point estimates suggest that downloads decrease while revenue increases, though both estimates are noisy. It is possible that these results are driven by endogeneity, though we note in the Appendix that the parallel trends assumption is most likely to be satisfied using this comparison group. We conclude that either the effect is indeed close to zero or that the power offered by the use of this control group is insufficient to detect a non-zero change in outcomes.

## 5.2 Using Apps distributed by Apple's App Store as Control

It is possible that other events occurring on Google's Play store concurrent with the policy change in Korea could confound the results of the previous subsection. We thus explore the use of apps distributed by Apple's App Store as an alternative control. As not every app chooses to multihome, our dataset is restricted to four apps. We estimate Equation (4) while restricting our data to apps in South Korea, and estimate Equation (5) using variation in both countries and platforms.

The results are reported in Table 5. As above, the point estimates suggest that downloads decrease, though revenue increases. However, also as above, the coefficients are estimated with noise. These estimates alone do not allow us to conclude that the policy affected outcomes.

**Table 4: Results using apps in other countries as controls**

| | *Dependent variable:* | |
|---|---|---|
| | log(downloads) | log(revenue) |
| | (1) | (2) |
| Post*Treat | $-0.186$ | $0.243^{*}$ |
| | (0.096) | (0.121) |
| Fixed effects | | |
| App | Y | Y |
| Week | Y | Y |
| Month | Y | Y |
| Year | Y | Y |
| Number of apps | | |
| Play-distributed | 9 | 9 |
| App Store-distributed | 0 | 0 |
| Countries | All | All |
| Observations | 7,562 | 7,562 |
| $R^2$ | 0.697 | 0.611 |

*Notes:* $^{*}$p<0.05; $^{**}$p<0.01; $^{***}$p<0.001. Standard errors are in parentheses. The reported coefficients are estimates of the interaction term between post treatment period and treatment group from Equation (1), using nine Play-distributed apps installed in Korea and four other countries. The dependent variables are the logged number of installs in Column (1) and logged revenue in Column (2).

**Table 5: Results using apps on Apple App Store as controls**

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | log(downloads) | | log(revenue) | |
| | (1) | (2) | (3) | (4) |
| Play Store*Post | | 0.019 | | -0.120 |
| | | (0.111) | | (0.140) |
| Play Store*Korea*Post | -0.173 | -0.182 | 0.132 | 0.018 |
| | (0.148) | (0.245) | (0.169) | (0.310) |
| Fixed effects | | | | |
| App | Y | Y | Y | Y |
| Week | Y | Y | Y | Y |
| Month | Y | Y | Y | Y |
| Year | Y | Y | Y | Y |
| Countries | Korea | All | Korea | All |
| Play-distributed | 4 Apps | 4 Apps | 4 Apps | 4 Apps |
| App Store-distributed | 4 Apps | 4 Apps | 4 Apps | 4 Apps |
| Estimator | DiD | Triple | DiD | Triple |
| Observations | 1,127 | 5,624 | 1,127 | 5,624 |
| $R^2$ | 0.719 | 0.600 | 0.791 | 0.658 |

*Notes:* $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$. Standard errors are in parentheses. The sample used for DiD is restricted to four apps installed in South Korea that multi-home both app distribution platforms. The second and the fourth columns list the results of using the triple difference estimator. The sample size in these columns increases by five fold as they includes observations from other countries.

## 5.3 Using Play-distributed Apps in South Korea in the Pre-treatment Period as Control

It is possible that seasonal trends in the app markets could affect the results presented above. We therefore explore a third potential control: the performance of apps on Google Play a year prior to the implementation of Korea's policy. We explore this two ways. First, we focus on South Korea and estimate the differences in app behavior using different time periods using Equation (4). We then relax this restriction and estimate Equation (5) while considering different years as the different 'platforms.'

Table 6 reports the results. As above, the point estimates indicate that downloads decreased, though they are estimated with noise. The results for revenue, however, are not consistent across specifications. The difference-in-difference estimate indicates the revenue fell, whereas the triple-difference estimator indicates the opposite. Both of these estimates are noisy, however, and so this is perhaps unsurprising.

## 5.4 Discussion and limitations

Taken together, these results suggest that the policy may have resulted in a decreased number of installs for apps on Google's Play Store in South Korea, though we consider this result to be suggestive only. As the estimates of the effect of the policy change on revenue have inconsistent signs, we do not draw any conclusions about the empirical effects on revenue, even "suggestive" conclusions.

These results are perhaps unsurprising given South Korea's position in the app market globally. While the apps we investigate have different rankings across South Korea and the United States, all are within the top 100 for both countries. Given that the installed base of smartphone users in the United States is approximately an order of magnitude higher than in South Korea (and the number of smartphone users worldwide is another order of magnitude higher), it is reasonable to believe that firms facing high development costs would choose not to invest in implementing alternative payment systems even in the context of South Korea's law.

It is important to note that our analyses are subject to limitations. First, our identification

**Table 6: Regression using historical app performance as controls**

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | log(downloads) | | log(revenue) | |
| | (1) | (2) | (3) | (4) |
| Treat Year*Post | | 0.209** | | -0.240* |
| | | (0.073) | | (0.093) |
| Treat Year*Post*Korea | -0.064 | -0.276 | -0.153 | 0.076 |
| | (0.090) | (0.159) | (0.084) | (0.204) |
| Fixed effects | | | | |
| App | Y | Y | Y | Y |
| Week | Y | Y | Y | Y |
| Month | Y | Y | Y | Y |
| Year | Y | Y | Y | Y |
| Countries | Korea | All | Korea | All |
| Play-distributed | 9 Apps | 9 Apps | 9 Apps | 9 Apps |
| App Store-distributed | 0 | 0 | 0 | 0 |
| Estimator | DiD | Triple | DiD | Triple |
| Observations | 1,496 | 7,562 | 1,496 | 7,562 |
| $R^2$ | 0.582 | 0.445 | 0.571 | 0.262 |

*Notes:* *p<0.05; **p<0.01; ***p<0.001. Standard errors are in parentheses. The sample used for DiD is restricted to nine Play-distributed apps installed in South Korea. ‘Treat Year’ is treated year, where year is redefined to start from June of each calendar year. Post represents treated months (months of post treatment), which are December, January, and February. The post treatment period is from December 2021 until the most recent date in the data, which is February 2022.

strategies assume that no event (other than the policy change) systematically affected outcomes for apps distributed on the Google Play Store in South Korea during the analysis period. Second, the small sample size of our data (in particular the small number of apps overall) implies that our results may be susceptible to outliers, weakening external validity. We note that we focus on the top grossing apps that have higher incentives and financial capacity to implement different in-app billing system if it produces significant benefit and thus if these big apps do not change their billing system, it is highly unlikely that the smaller apps switch as their incentive to do so may be even lower.

# 6 Conclusion

The near-monopoly power of the two leading app distribution platforms have raised antitrust concerns that these platforms leverage their market power to tie in-app billing system with their platform operations and charge developers a dictated commission rate that is higher than would be present in a more competitive market. To prevent leading platform operators from monopolizing in-app billing system, the National Assembly of South Korea recently passed a law that bans app stores from requiring developers to only use the platform's billing system, i.e., preventing app marketplace operators from tying in-app billing system with their platforms. This research serves as a preliminary study to examine the short-term effect of this legislation. We examine whether Google Play's response to the legislation has any significant impact on app demand as well as app revenue. While the previous literature has largely focused on negative market consequence of tying (reducing incentives to innovate, price that is charged higher than competitive rate, etc.), the effects of unbundling are less well-studied. Our study is among the first to investigate the market consequence of decoupling in-app billing system from operation of app distribution platforms.

Across specifications, we observe a consistently negative point estimate of the relationship between the reform and the number of downloads, and an inconsistent relationship between the reform and app revenues. These effects are estimated with substantial noise, however, and we therefore conclude that the policy change was unlikely to significantly affect app performance in South Korea over the period we consider. We note that any quality improvement of an app as a result of cost reduction is likely to be not immediate, which may be the reason we do not see positive policy shock on app demand as we have anticipated. In other words, it may simply be too early to derive any concrete conclusions about the policy effect.

It could also be the case that we do not observe expected policy effect due to practical reasons. There have been ongoing controversies that Google has not yet fully embraced the policy, i.e., they still charge 26% commission rate for developers moving their in-app billing system away from the platform's billing system. This gives less incentives for developers to change their behaviors as the benefit of changing might not be so high or even lower. It could also be that Google's still great market power in platform market formulates significant switching cost among developers, which means without sufficient government support and collective actions of developers, it is still hard for them to opt-out from Google's billing system (Hwang and Kim 2022). In a way, our results may be expected.

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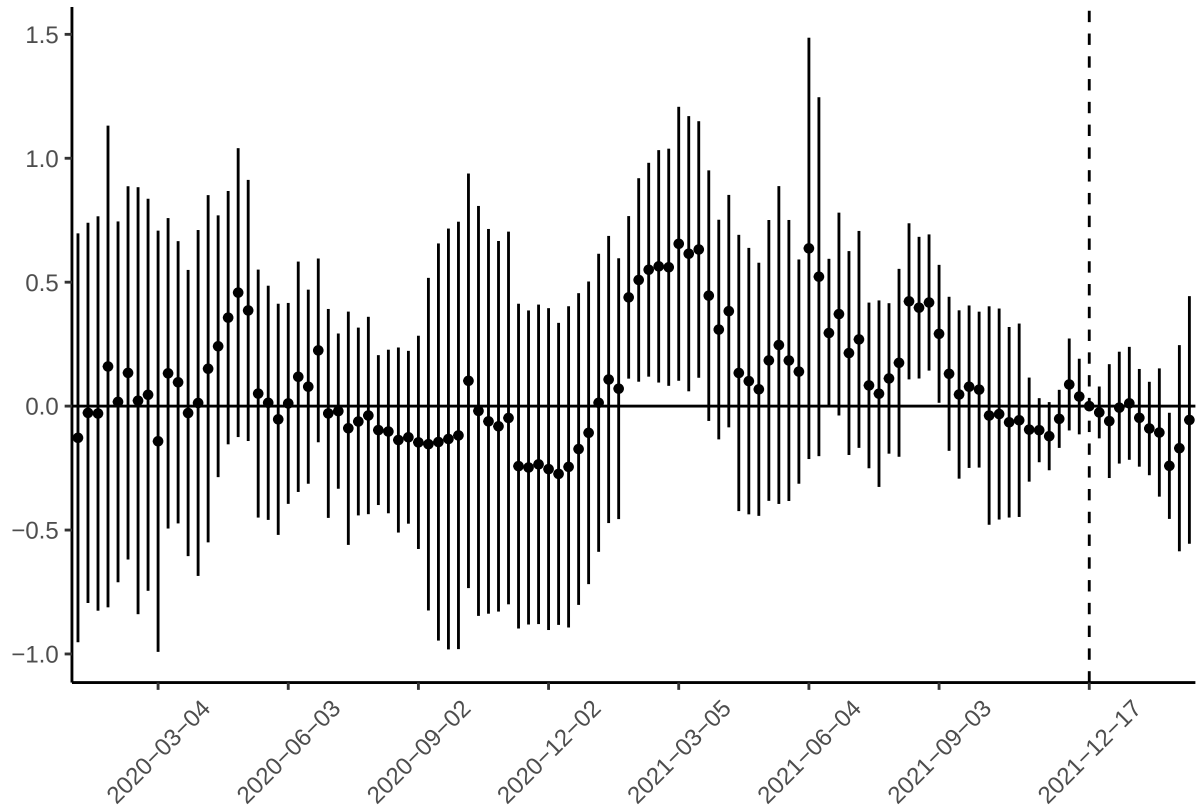
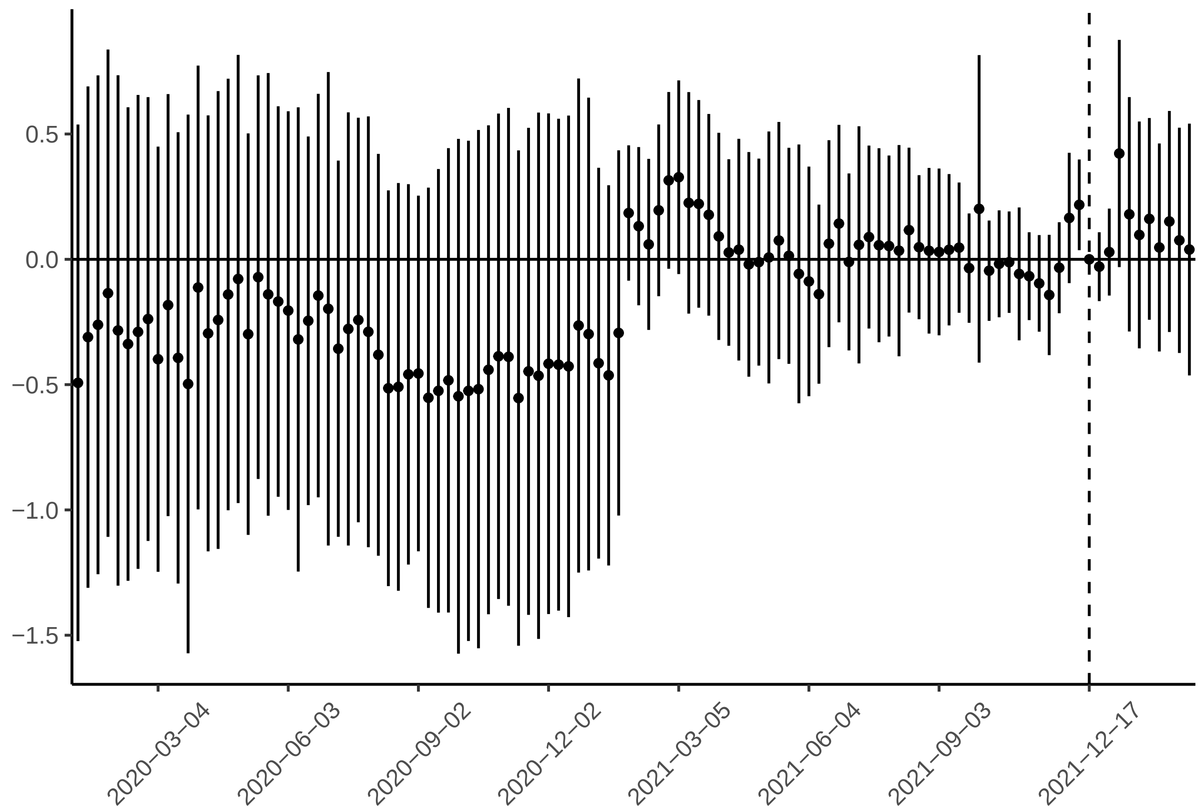
# Appendix

**Figure A.1: Event study of Google's response on the number of app installs**



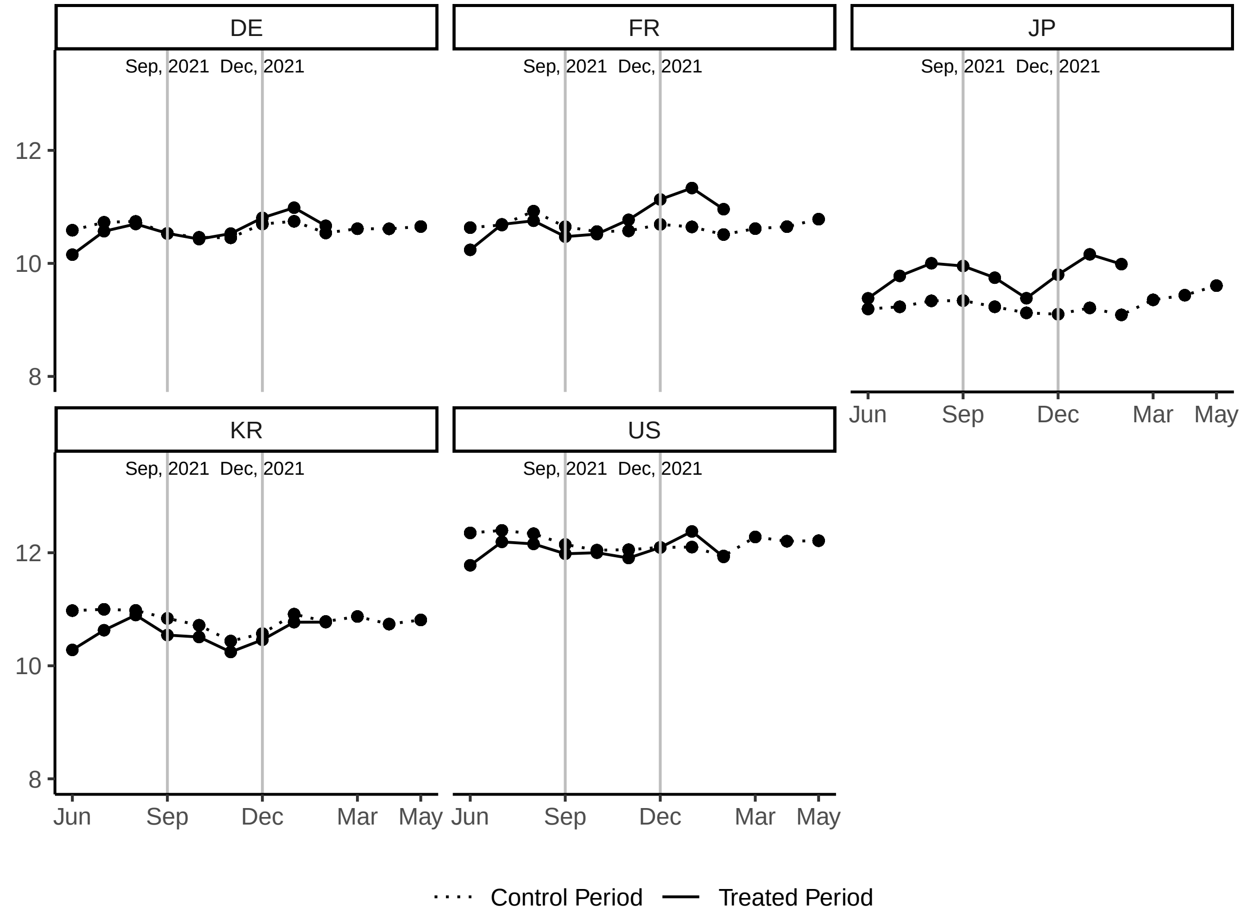

*Note:* These estimates are from an event study regression. The dependent variable is logged number of downloads and the independent variables include app, country, and time fixed effects. The reference week is set on the week of December 18, 2021. Standard errors are clustered at the app level.

**Figure A.2: Event study of Google's response on app revenue**



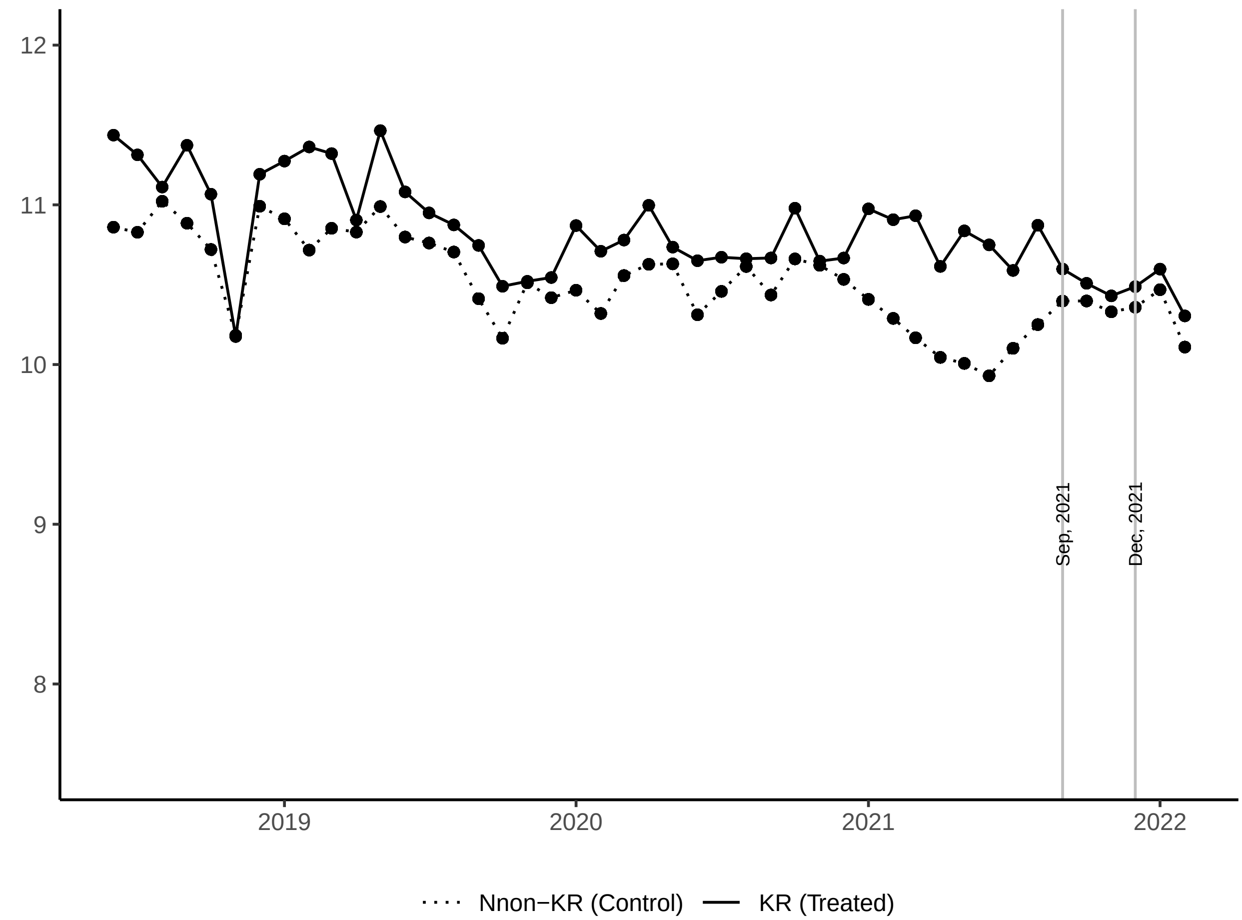

*Note:* These estimates are from an event study regression where the dependent variable is logged app revenue and the independent variables include app, country, and time fixed effects. The reference week is set the week before December 18, 2021. Standard errors are clustered at the app level.

**Figure A.3: New Installs Trend of the Apps in Treated and Control Period by Country**



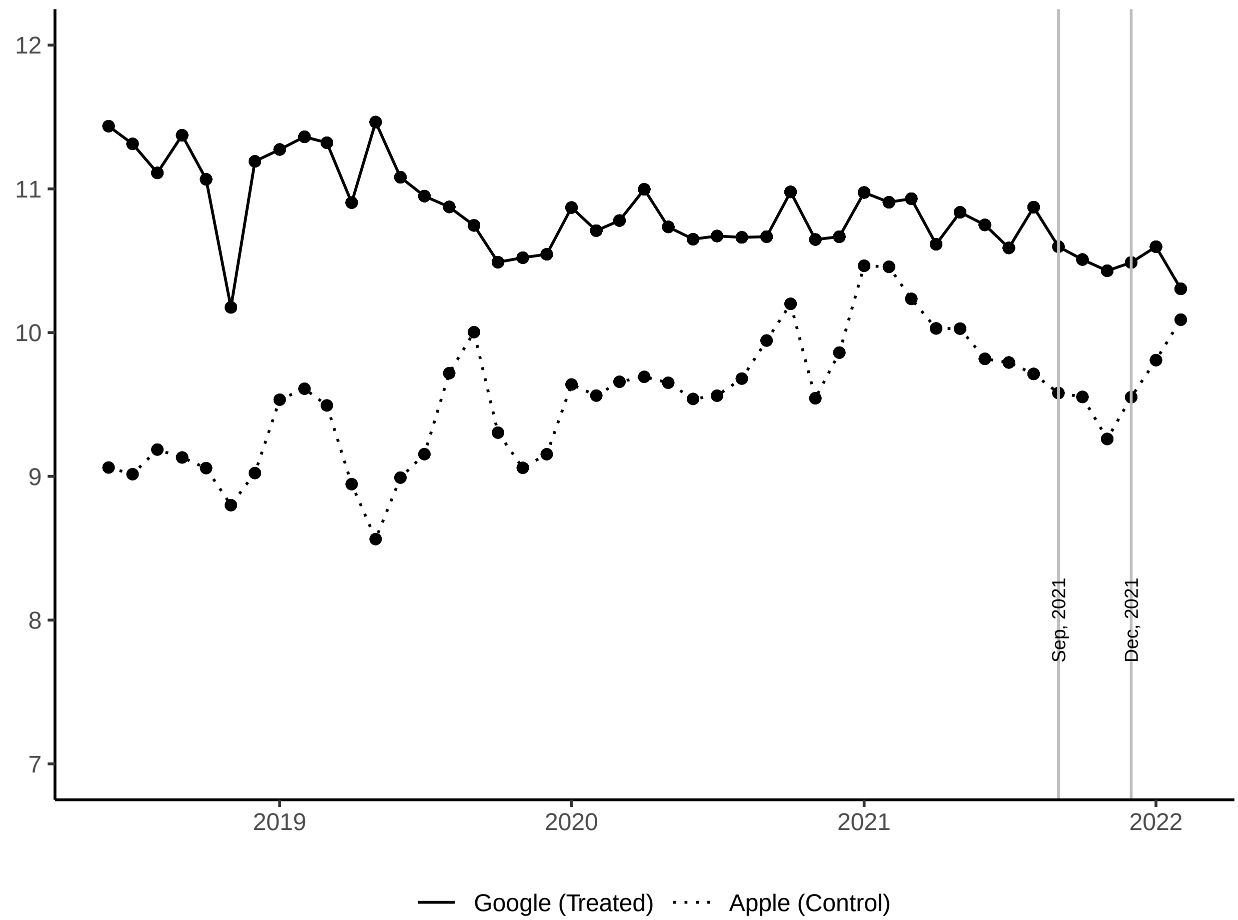

*Note:* This figure illustrates new install trends of the apps in the treated and the control period investigated at country-level. The solid line represents average app demand in the sample during the treated period, three-month prior to the legislation until February 2022. The vertical lines each represents the timing of the legislation and Google's policy reform that accommodates the opening mobile in-app billing system. The x-axis represents month while the y-axis represents monthly aggregated averaged logged number of new installs of the four apps that have long enough time series data that start from 2018. The plot does not consider the remaining five apps in calculating the monthly averages as this may contaminate comparison across months and across different periods.

**Figure A.4: New Installs Trends of the Apps in Treated and Control Countries**



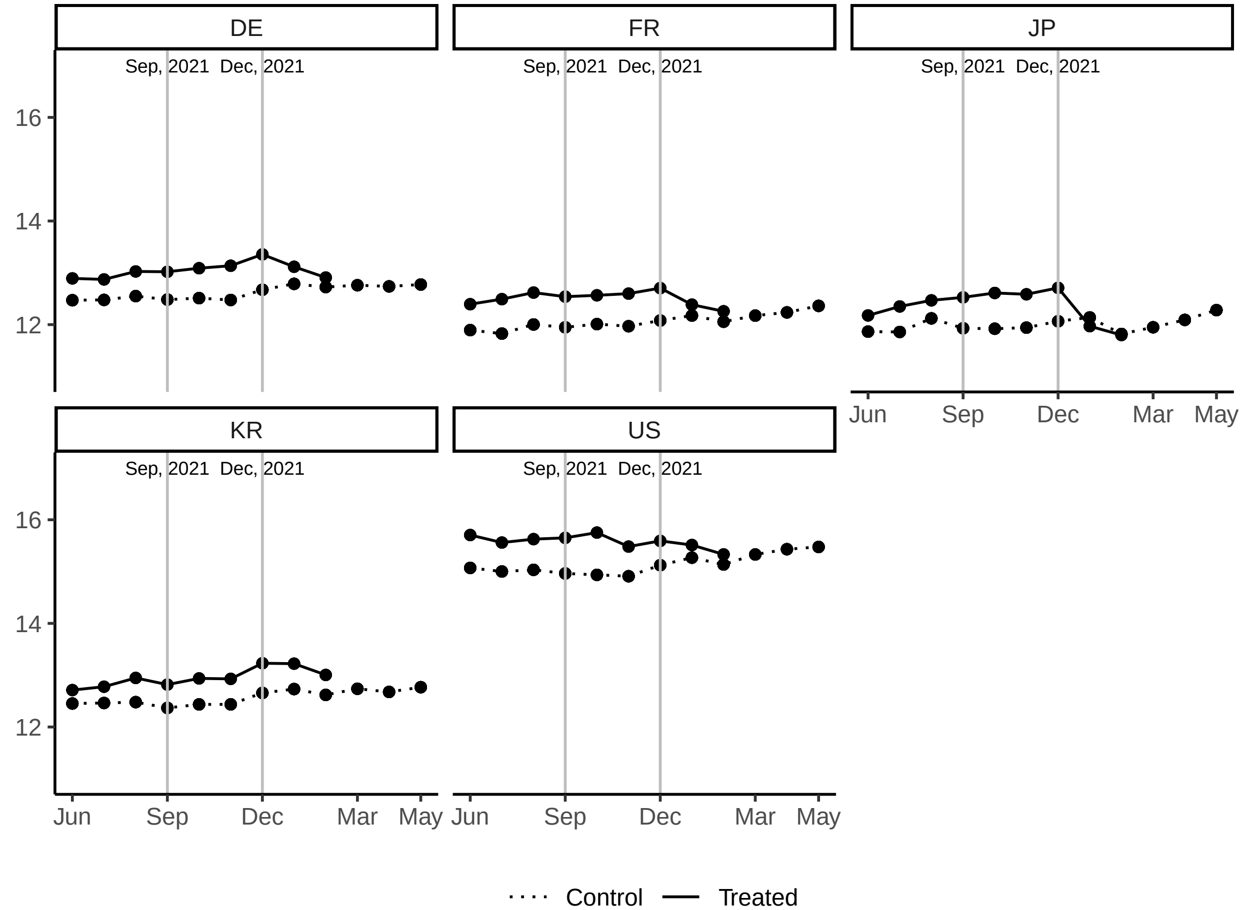

*Note:* This figure illustrates new install trends of the apps in the treated and the control countries. The solid line represents the app demand in the sample from the treated country, Korea, whereas the dotted line is the monthly number of new downloads averaged across apps and across non-Korea countries in the sample. The vertical lines each represents the timing of the legislation and Google's policy reform that accommodates the opening mobile in-app billing system. The x-axis represents time while the y-axis represents monthly aggregated averaged logged number of new installs of the nine Play apps.

**Figure A.5: New Installs Trends of Apps on the Treated and Control Platform**



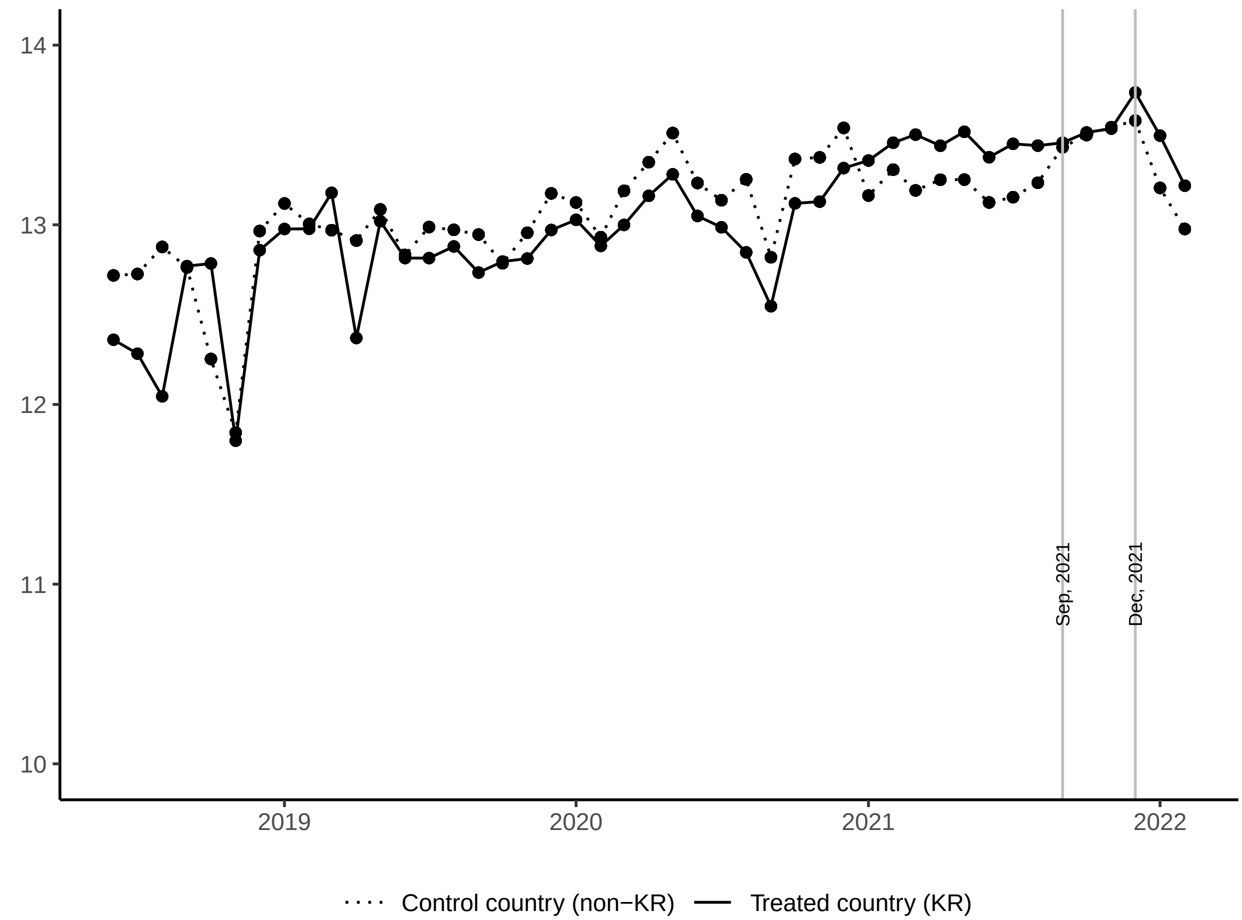

*Note:* This figure illustrates new install trends of the apps in the treated and the control platforms. The solid line represents the app demand in the sample from the treated platform, Google Play, whereas the dotted line is the monthly number of new downloads averaged across apps on Apple App Store. The vertical lines each represent the timing of the legislation and Google's policy reform that accommodates the opening mobile in-app billing system. The x-axis represents time while the y-axis represents monthly aggregated averaged logged number of new installs of the four App Store apps and nine Play apps.

**Figure A.6: Revenue Trends of the Apps in Treated and Control Periods by Country**



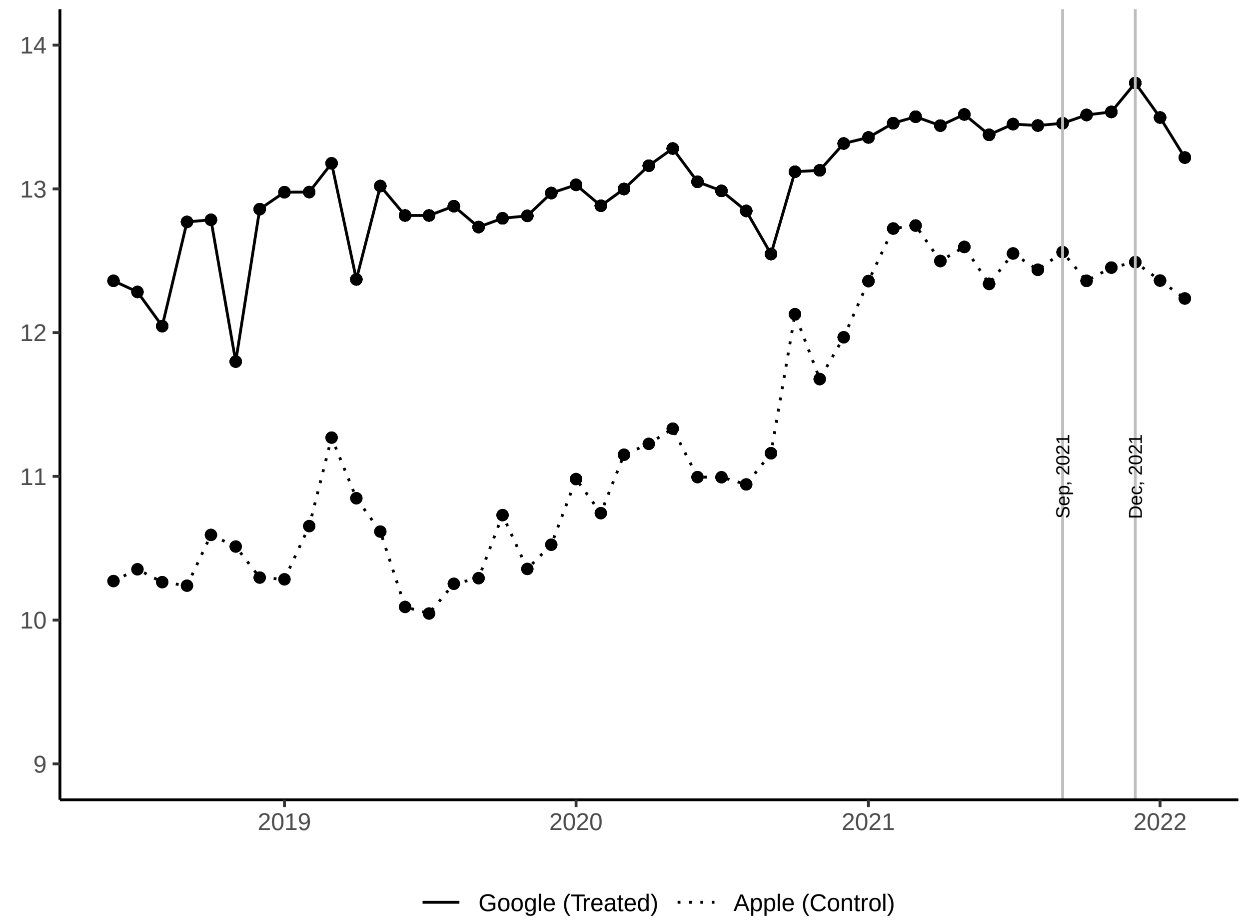

*Note:* This figure illustrates revenue trends of the apps in the treated and the control period investigated at country-level. The solid line represents average app revenue in the sample during the treated period, three-month prior to the legislation until February 2022. The vertical lines each represents the timing of the legislation and Google's policy reform that accomodates the opening mobile in-app billing system. The x-axis represents month while the y-axis represents monthly aggregated averaged logged revenue of the four apps that have long enough time series data that start from 2018. The plot does not consider the remaining five apps in calculating the montly averages as this may contaminate comparison across months and across different periods.

**Figure A.7: Revenue Trends of Apps in the Treated and Control Countries**




*Note:* This figure illustrates revenue trends of the apps in the treated and the control countries. The solid line represents the average app revenue in the sample from the treated country, Korea, whereas the dotted line is the monthly revenue averaged across apps and across non-Korea countries in the sample. The vertical lines each represent the timing of the legislation and Google's policy reform that accomodates the opening mobile in-app billing system. The x-axis represents time while the y-axis represents monthly aggregated averaged logged revenue of the nine Play apps.

**Figure A.8: Revenue Trends of Apps on Treated and Control Platform**




*Note:* This figure illustrates revenue trends of the apps in the treated and the control platforms. The solid line represents the average app revenue in the sample from the treated platform, Google, whereas the dotted line is the monthly revenue averaged across apps on Apple App Store. The vertical lines each represent the timing of the legislation and Google's policy reform that accomodates the opening mobile in-app billing system. The x-axis represents time while the y-axis represents monthly aggregated averaged logged revenue of the four App Store apps and nine Play apps.