Merger Policy for Platforms: A Growth Theory Perspective*

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Abstract

Should Big Tech firms be allowed to acquire other firms? We address this question by developing a model of platform-based consumption. The platform supplies some of the products in the economy and startups supply the rest. The platform shares only part of its appeal with startups ("tying"), balancing the incentive to increase sales of its own products against the desire to attract consumers to the platform. The chance to be acquired by the platform provides a motive for startup entry. But acquisitions also expand the platform's product offerings, increase tying, and lower the profits of non-acquired startups which are the other motive for entry. Theoretically, an acquisition ban reduces growth in the short run but may increase it in the long run. Calibrating the model to data on U.S. households' time use on digital platforms suggests very minor welfare gains from an acquisition ban.

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1 Introduction

Policymakers are increasingly focused on competition and growth in digital markets. Legislation in the United States, United Kingdom, and European Union has singled out the acquisitions of the "GAFAM" (Google, Amazon, Facebook, Apple, and Microsoft) firms for scrutiny or even bans because of their role as ''gatekeepers" or ''covered platforms." Much of the concern among regulators is about the effect of these acquisitions on economic growth, in contrast to the longstanding approach of competition authorities to evaluate static tradeoffs between increased market power and greater efficiency when designing merger policy (OECD 2023).

Because platform technologies are new, and because competition authorities have only recently begun to consider the dynamic effects of merger policy, there is a lack of economic theory about the effects of platform acquisitions on growth. This paper aims to fill this gap by developing an endogenous growth model with platform-based consumption. Our framework allows us to assess competing views about the role of platform acquisitions in spurring entry. One view is that the chance to be acquired creates an extra incentive for startup founders on top of the profits they expect to generate as a standalone firm, so-called "entry for buyout" (Rasmusen 1988; Fons-Rosen, Roldan-Blanco, and Schmitz 2024). On the other hand, the presence of a dominant "digital ecosystem" with many integrated products and services sold by a platform may make it hard for standalone firms to make profits in the first place (Khan 2017).

The paper makes two main contributions. The first is to develop a novel model where platform acquisitions have both positive and negative effects on growth to capture the *dynamic* tradeoffs regulators face. The second is to bring the model to the data to see which effect dominates. The negative ecosystem dominance effect on entry is slightly stronger than the positive option value of acquisition effect. The welfare change from an acquisition ban is therefore positive in the baseline calibration, around 0.08% of consumption-equivalent welfare. However, the welfare effect of an acquisition ban can turn negative with small and reasonable changes to key model parameters. Alternative competition policies, like prohibiting self-preferencing of the platform's own products in search results or requiring interoperability between the platform and third party sellers, can improve welfare much more than an acquisition ban without hampering entry.

The model features two activities by platforms that regulators are concerned about. The first is acquisitions of other firms. The second is product tying, a term we use to encompass a broad range of behaviors platforms can engage in that tilt consumption toward their own products relative to goods sold by third parties on the platform. For example, a platform can display its own products prominently in search results (Waldfogel 2024), reduce the quality of competing apps by limiting interoperability (Morton 2023), or bundle products and services into its existing digital ecosystem (Choi 2010).[1]

Using the platform provides utility benefits to households, some of which depend on the overall intensity of use of the platform (capturing network effects), and some of which do not (such as reduced search costs). Households take as given the number and quality of products available on the platform and choose how much to use the platform each period. The platform firm faces a tradeoff when it decides how much to engage in product tying. Tying increases the attractiveness of the platform's products relative to third-party products, thus increasing profits on each product line the platform owns. On the other hand, it discourages households from using the platform altogether, which depresses demand, lowering sales and profits.

The platform adds new goods to its product portfolio by acquiring standalone firms, who we call startups. When the platform engages in tying, such meetings generate a surplus and both parties would like to merge. From a consumer perspective, acquisitions increase the quality of the target firm's product and the target's sales increase post-acquisition. If this were the only effect of acquisitions, they would be unambiguously good for consumers. However, the model also captures an "ecosystem dominance" theory of harm: acquisitions make it less costly for the platform to engage in tying because households have a greater incentive to use the platform when it supplies a larger share of the products in the economy.

The first theoretical result is that platform acquisitions have ambiguous effects on entry (and thus growth and welfare) in the long run. On one hand, the option value of acquisition induces more entry by startups. On the other hand, new to our paper, acquisitions increase tying, lowering startups' standalone value before acquisition and discouraging entry. We derive a condition such that an acquisition ban has positive long-run effects on growth. An acquisition ban is more likely to increase growth when the option value of acquisition is low compared to the responsiveness of standalone profits to ecosystem dominance. These two channels can be directly linked to measurable objects in the data.

The second result is that, even if an acquisition ban increases growth in the long run, it necessarily involves sacrificing growth in the short run because entry for buy-

[1]See Motta (2023) for a summary of such practices.

out incentives change immediately while the costs of tying diminish slowly as the platform's ecosystem dominance erodes through the entry of new startups. This result leads us to focus on transition paths rather than steady-state comparisons when evaluating different competition policies.

The model has one novel parameter, the platform's appeal technology, that we calibrate using the model's mapping from this technology parameter to household time spent using the platform. In the calibrated model an acquisition ban increases steady state consumption-equivalent welfare by 0.18% by increasing the steady state entry rate. However, because a ban reduces entry in the short run, the properly discounted welfare *over the transition* increases by just 0.08%. For slightly higher values of startup bargaining power in merger negotiations or lower values of the platform technology parameter, which both seem plausible, the welfare effect of an acquisition ban over the transition is negative. A ban on tying yields significantly higher welfare gains than an acquisition ban, primarily by correcting platform under-utilization due to tying in the competitive equilibrium but also by increasing the entry rate.

We consider two extensions of the model. In an extension where the platform sells its appeal to startups as a service rather than changing their appeal directly through tying, we provide an alternative micro-foundation for the tying mechanism. The platform chooses a markup on its service that is even higher than the standard monopolistic markup to boost sales of its own products. This strategic incentive is the same as in the baseline model.

In a second extension with idiosyncratic productivity shocks and exit, the platform generates negative selection. Tying raises the platform's profits on low-productivity goods and makes them less likely to be shut down, whereas startups shut down too quickly from a planner's perspective. OECD (2023) emphasizes the importance of considering this sort of quality effect in digital markets since network effects and ecosystem dominance make it hard to displace low-quality incumbents.

A final contribution of the paper is to document new stylized facts about platform firms and their acquisitions. The cross-industry acquisitions we study constitute about 70% of all platform acquisitions. These acquisitions span a large set of industries: 61% of all U.S. industries experienced at least one platform acquisition between 2010-2020. Lastly, we provide measures of the aggregate importance of platforms based on retail sales, revenues, stock market valuations, and time use surveys.

Related Literature. This paper is related to two strands of literature in macroeconomics. The first studies the market for firms and its effects on firm dynamics, growth, and welfare.[2] The most closely related paper is Fons-Rosen, Roldan-Blanco, and Schmitz (2024), who analyze the growth effects of acquisitions when incumbents have a commercialization advantage for new ideas but may "kill" competing products in the same industry.[3] Our contribution is to introduce a new mechanism about cross-industry acquisitions, which account for 70% of platform acquisitions in recent years, into the discussion. In our model, the platform is special because it provides a service that is complementary to all goods in the economy. Acquisitions enhance the quality of the acquired product and are bilaterally efficient, but have negative spillovers to non-acquired firms due to increased ecosystem dominance. We view our work on cross-industry acquisitions as complementary to the literature on killer acquisitions.

The second literature we contribute to studies the emergence and welfare effects of platforms[4] and of digital technologies more broadly.[5] Rachel (2024) models how the rise of digital platforms altered the direction of innovation toward leisure technologies. Greenwood, Ma, and Yorukoglu (2024) and Cavenaile et al. (2023) study the welfare implications of targeted digital advertising. Dolfen et al. (2023) measure how the growth of e-commerce benefited consumers through better consumer-firm matches and lower search costs. Our primary contribution is to model product tying, a key feature of platforms' strategic behavior, and to use a dynamic general equilibrium model to understand the way that tying and acquisitions interact to affect entry.

There is also a body of partial equilibrium studies of mergers and acquisitions (M&A) in digital markets.[6] Our model formalizes Cabral (2021)'s argument that

[2]See Atalay, Hortaçsu, and Syverson (2014), David (2020), Bhandari and McGrattan (2020), Bhandari, McGrattan, and Martellini (2025), Weiss (2023), Celik, Tian, and Wang (2022), Chatterjee and Eyigungor (2023), Liu (2023), Berger et al. (2025). Relatedly Akcigit, Celik, and Greenwood (2016) study the market for patents and Pearce and Wu (2023) study the market for trademarks. These papers, and ours, build on insights from earlier research about motives for mergers ranging from capital reallocation, complementarities between firms, and economies of scale (Jovanovic and Rousseau 2002; Rhodes-Kropf and Robinson 2008; Hoberg and Phillips 2010; Mermelstein et al. 2020).

[3]See also Cunningham, Ma, and Ederer (2020) and Kamepalli, Rajan, and Zingales (2020).

[4]See Rochet and Tirole (2003) and (2006), Brynjolfsson, Chen, and Gao (2025), and Alvarez et al. (2025).

[5]On data, see Begenau, Farboodi, and Veldkamp (2018), Jones and Tonetti (2020), Beraja, Yang, and Yuchtman (2022), Farboodi and Veldkamp (2023). On digital advertising, see Acemoglu et al. (2024), and Baslandze et al. (2023).

[6]There is work on the theoretical side (Bryan and Hovenkamp 2020; Motta and Peitz 2021; Eisfeld 2023; Heidhues, Köster, and Kőszegi 2024) and the empirical side (Warg 2023; Ederer and Pellegrino 2023; Hoberg

merger policy is a blunt tool to address competition in digital industries. Kaplow (2021) calls for a multi-sector, dynamic analysis of digital merger policy because acquisitions can create cross-industry distortions. We develop and quantify such a model.

Beyond merger policy, Evans and Schmalensee (2014) summarize antitrust issues, including tying, in platform-based markets.[7] Gutiérrez (2023) provides a case study of Amazon's fee structure and analyzes the welfare effects of separating Amazon's retail and platform businesses. Several papers study competition, interoperability, and fee design among different platforms.[8] While we abstract from many of these interesting issues in service of parsimony, we bridge the gap between this literature and the growth literature by incorporating platform tying into a growth model.

2 Platforms: Recent Trends

Two trends inform our analysis. First, platform-based firms have acquired other firms in a large and diverse set of industries. Second, to motivate a general equilibrium model of consumption through a platform, we provide evidence that such consumption is becoming an important share of overall economic activity.

Cross Industry Acquisitions. The SDC Platinum Database records the universe of M&A deals over \$1 million involving U.S. firms from 1990 onwards. Information on each deal includes the acquirer name, target name, transaction price, industry classification and some financial information for publicly listed parties. To this dataset we add VentureXpert data on target age and number of employees and use a fuzzy matching procedure to add data on patents from the U.S. Patent and Trademark Office.[9] We focus on GAFAM, motivated by the policy discussion around these particular firms because of their role as platforms, but compare the statistics for GAFAM to the same statistics for other large acquirers. The sample period is 2010-2020.

and Phillips 2024).

[7] See also Fumagalli and Motta (2020) and Ide and Montero (2024).

[8] See Athey and Morton (2022), Lu, Goldfarb, and Mehta (2024), Jeon and Rey (2024), and Ekmekci, White, and Wu (2024).

[9] Appendix Table A.1 provides summary statistics about platform-based firms' acquisitions and contrasts them with deal and target characteristics for other large acquirers. The platforms did more acquisitions on average from 2010-2020 compared to other large acquirers, acquired younger targets, and acquired targets with a higher chance of having patents and lower chance of having positive earnings prior to acquisition.

	GAFAM	Top 25 Tech	Top 25 PE	Top 25 S&P
NAICS6, %	83	81	64	61
SIC4, %	74	79	65	60
SDC Tech. Class., %	69	59	48	46
B2C Targets, %	27	8	3	3
Number of deals	467	1114	3790	3498

Table 1: Percent of acquisitions where acquirer (and acquirer's ultimate parent) and target have different primary industry codes. "GAFAM": Google, Apple, Facebook, Amazon, and Microsoft. Other groups are constructed following Jin, Leccese, and Wagman (2023a): the largest non-GAFAM acquirers in Forbes' ranking of Top 100 Digital Companies ("Top 25 Tech"), the largest private equity firms by Private Equity International ("Top 25 PE") and the other largest 25 firms by number of acquisitions in the S&P database ("Top 25 S&P"). Source: SDC Platinum, 2010-2020 and Jin, Leccese, and Wagman (2023a) for B2C targets data.

Most GAFAM acquisitions are cross industry, regardless of the specific way we define an industry (Table 1, column 1). The most conservative definition, the SDC Platinum's own classification scheme, gives a cross-industry share of 69%. Using 6-digit NAICS gives a cross-industry share of 83%. Comparing GAFAM to other large acquirers shows that they are *more* likely than other acquirers to engage in cross industry acquisitions. Our findings are consistent with previous evidence that only a small fraction of Big Tech targets operated a platform or other competing service (Argentesi et al. 2020; Parker, Petropoulos, and Alstyne 2021; Jin, Leccese, and Wagman 2023a; Jin, Leccese, and Wagman 2023b). Platform firms are also much more likely than others to acquire purely "B2C" firms, that is, final goods producers. Prominent examples of cross-industry acquisitions include Google's acquisition of FitBit, Amazon's acquisitions of Whole Foods, MGM Studios, and iRobot, and Microsoft's acquisition of LinkedIn. Google's first acquisitions in 2004 of Where2, Keyhole, and ZipDash enabled the creation of Google Maps.

Platform acquisitions are important from a macroeconomic perspective and impact a broad swath of industries; 61% of all NAICS4 industries in the U.S., accounting for 55% of GDP, experienced at least one GAFAM acquisition between 2010 and 2020, suggesting that acquisitions reach well beyond closely related digital services firms.

Importance of Platforms in the Economy. Measuring the share of economic activity that flows through platforms is challenging. We present several measures of the importance of platform-based firms and discuss the limitations of each.

One possible measure is e-commerce. Since 2000, e-commerce retail sales have grown 16% per year, compared to 4% for total retail sales. e-commerce now accounts for 16% of all retail sales and continues rapidly expanding. Retail sales in turn account for about 10% of total private final consumption expenditure. Not all e-commerce is done through platforms, so this may overstate the importance of platforms, though Amazon alone controls 40% of the U.S. e-commerce market (Forbes 2024).

On the other hand, Big Tech firms do not just sell to final consumers, they also sell their products, such as Microsoft Office or Amazon Web Services, to other firms, which is missed in retail sales. Taking a broader view based on total revenues, the share of these five companies in total U.S. non-farm, non-financial corporate revenues was 11% in 2021.[10]

A final way to measure the significance of digital platforms is time use (Rachel 2024). A representative survey from Nielsen's (2021) for the U.S. population shows 3.8 total hours spent online each day between computers and mobile devices. A different 2023 survey found that U.S. users spent 4.2 hours per day on various social media platforms (Emarketer 2023). Restricting attention to online shopping, households spend a little over an hour per week (SWNS 2024). When we bring the model in the next section to the data we match the platforms' share of total revenue and explore the effect of an acquisition ban under various targets for platform time use.

3 Baseline Model

The economy consists of a growing mass of products whose consumption by households is intermediated by a platform. An online retail platform like Amazon is a natural example.[11] Some products are produced by the platform itself (e.g. Ama-

[10]One way to assess how important these firms are *expected* to be in the future is to use price to equity ratios to infer future earnings growth as in Boppart et al. (2024). The GAFAM firms are all among the top ten firms expected to contribute the most to future earnings growth. As of March 2025 these five companies had a combined market capitalization of $12 trillion and made up 25% of the S&P500.

[11]Other examples include app stores operated by Apple, Microsoft and Google, the integration of third party mobile games and apps into Facebook's platform alongside Facebook-owned apps like Instagram and WhatsApp, or streaming platforms like Netflix that offer their own content alongside third party content.

zon Basics) and the rest are sold by third party sellers who we call startups. Households choose how much time to spend using the platform, with greater use improving the shopping experience but incurring a time cost. Potential new startups make a forward-looking entry decision. Time is continuous.

3.1 Environment

Household. A representative household supplies L_t total units of labor and derives utility from real consumption C_t. The household's discounted utility is given by:

$$\int_0^\infty e^{-\rho t} \left[\log C_t - L_t\right] dt. \tag{1}$$

Real consumption is aggregated across products $i \in [0, N_t]$, where N_t is the measure of products available at time t, using a constant elasticity of substitution (CES) aggregator. Specifically,

$$C_t = \left[\int_0^{N_t} \alpha_{it}^{\frac{1}{\sigma}} c_{it}^{\frac{\sigma-1}{\sigma}} di\right]^{\frac{\sigma}{\sigma-1}}, \tag{2}$$

where $\sigma > 1$ is the elasticity of substitution across products, c_{it} is the quantity, and α_{it} is a demand shifter related to the platform's intermediation role that we explain shortly.

Labor L_t is devoted to three activities. Among these activities, $L_{Y,t}$ is used for production of consumption goods and $L_{E,t}$ is used to start new businesses, both of which earn labor income to the household. The remaining $L_{P,t}$ is spent using the platform, which does not earn labor income. Throughout the paper, the wage rate is normalized to 1. All three activities trade off with leisure time. The household owns a representative portfolio of all firms that pays out the aggregate profits as dividends. The household's budget constraint is thus

$$\dot{a}_t = r_t a_t + L_{Y,t} + L_{E,t} + \Pi_t - \int_0^{N_t} p_{it} c_{it} di,$$

where a_t is savings in the representative portfolio, r_t is the interest rate, Π_t is the aggregate profit of firms in the form of a dividend, and p_{it} is the price of product i.

Three results follow, derived in Appendix B.1. First, there is the Euler equation for consumption-saving decisions $r_t = \rho$. Second, the household's consumption decision implies a standard CES demand curve for each good:

$$c_{it} = \alpha_{it} \left[\frac{p_{it}}{P_t}\right]^{-\sigma} C_t, \tag{3}$$

where

$$P_t \equiv \left(\int_0^{N_t} \alpha_{it} p_{it}^{1-\sigma} di \right)^{\frac{1}{1-\sigma}} \tag{4}$$

is the quality-adjusted aggregate price index. Lastly, the perfectly elastic labor supply implies that aggregate expenditure is always $P_t C_t = 1$.

Production. The N_t products can be categorized according to their ownership at time t: N_{Pt} products are sold by the platform, and N_{St} products are sold by startups. Labor is the only input to production and all producers have a constant labor productivity of one.

Product Quality with Platform-Based Consumption. The key novelty of the paper is that the platform firm intermediates consumption of all products, in addition to its role as a producer. This intermediation process determines quality α_{it} for each good i in the following way

$$\alpha_{it} = \begin{cases} 1 + L_{P,t}\gamma & \text{platform products (P)} \\ 1 + L_{P,t}\gamma(1-\delta_t) & \text{startup products (S)} \end{cases}, \quad \delta_t \in [0,1]. \tag{5}$$

Each product has a baseline quality of 1 (e.g. the quality if bought offline). On top of this, the platform firm is endowed with a technology γ that increases the quality of products consumed through the platform (e.g. by reducing search costs). The technology γ complements household time spent using the platform $L_{P,t}$ (e.g. time use generates product ratings data which improves the shopping experience).

The platform decides how much of its technology γ to share with startups in a decision we call tying,[12] represented by δ_t. When there is no tying by the platform ($\delta_t = 0$), the platform technology is fully shared with startups and the goods look identical from a consumer perspective, whereas when $\delta_t > 0$ the startups have lower quality. The choice of tying represents a range of behaviors the platform can engage in to decrease the appeal of third-party products. For example, promoting its own products in search so that finding startup products takes longer (Waldfogel 2024), bundling platform-owned products together (OECD 2023), limiting sellers' access to data and back-end code to reduce interoperability (Kamepalli, Rajan, and Zingales

[12]Tying is used in industrial organization to refer to situations where two goods must be bought together. More recently, technical tying has been used to refer to design features, like integrated digital ecosystems, that make it difficult to consume one good without accessing another.

2020), or reducing the performance of third-party apps on the platform (Department of Justice 2024). Section 7.1 considers an alternative assumption that the platform sells its technology as a service to startups and faces a cost to providing these services, relaxing the assumption that sharing the platform's technology is costless. Similar strategic incentives arise in that alternative model.

Entry Dynamics. The measure of startups N_{St} grows when new startups enter and shrinks when existing startups are acquired by the platform. A large measure of potential entrants can create new startups using labor. The entry cost is declining in the stock of varieties N_t as in Romer (1990) and increasing in the growth rate of new varieties (Acemoglu et al. 2018; Klenow and Li 2025). More specifically, at time t, the entry cost is $\frac{\kappa(g_t)}{N_t}$ where

$$\kappa(g) = \kappa g^{\eta},$$

and $\eta \geq 0$. After entering the startup's product line stays in operation forever.[13] At $t = 0$, we assume the economy starts with N_0 products and $N_0 > 0$.

Acquisition Dynamics. The platform expands its product offerings N_{Pt} by acquiring startups through a frictional trading process. The platform meets individual startups at Poisson rate μ, which we refer to as the *acquisition rate*. Upon meeting, the platform and the startup decide whether to carry out the acquisition. If they agree, they engage in Nash bargaining over the joint surplus created by the acquisition, with bargaining power β for the startup. When the platform engages in some tying ($\delta_t > 0$), acquisitions improve the quality of the acquired product, capturing a form of synergies. An acquisition ban is modeled as regulators setting μ to zero by blocking all platform acquisitions.

Ecosystem Dominance. A core new endogenous object of our model is the share of platform goods

$$\iota_t \equiv \frac{N_{Pt}}{N_t}.$$

We call ι_t the *ecosystem dominance* of the platform. The platform's ecosystem is dominant if it sells a large share of total goods (e.g., having a wide range of products from clothing to electronics to cloud services to video streaming). Ecosystem dominance grows through acquisitions but shrinks as new startups are founded.

[13] An extension with productivity shocks and endogenous exit is developed in Section 7.2.

Discussion. Before characterizing the equilibrium of the model, we discuss the economic content of the model's new ingredients. First, we assume that the platform increases the product's intrinsic quality. This is a reduced-form representation of the role of platforms in the consumption process, which could encompass improved service quality or reduced shopping costs. An alternative way to model the platform is through greater production efficiency. Regarding theoretical predictions, the productivity model is isomorphic to the present model. Second, although our model has only one platform, this single platform does face competition. This competition comes from the substitution of consumption between platform-owned products and startup products, and household substitution between platform use and leisure.[14]

3.2 Equilibrium

This section first solves for the static pricing equilibrium to obtain firm profits, taking platform use and tying as given. Then we solve the more novel tying and platform use decisions. These two steps yield firm profits as a function of the platform's ecosystem dominance. The final step studies the evolution of ecosystem dominance ι_t and the growth rate g_t in the full dynamic equilibrium.

Pricing Equilibrium. In the baseline model, we assume that all products (regardless of whether the platform or a startup supplies them) compete in a monopolistically competitive manner. Section 6.1 considers the case where the platform prices its products jointly, leading the platform to charge a variable markup and creating an additional distortion from ecosystem dominance. [15]

A standard argument implies that all products are priced at a constant markup over marginal cost (in this case the wage, which is normalized to 1). Thus the price is simply $\frac{\sigma}{\sigma-1}$. Given these prices, the price index for the household can be rewritten

$$P_t = \underbrace{\frac{\sigma}{\sigma-1}}_{\text{markup}} \times \left(\underbrace{N_t}_{\text{love of variety}} \times \underbrace{\Big(1+\gamma L_{P,t}(\iota_t + (1-\iota_t)(1-\delta_t))\Big)}_{\text{platform}} \right)^{\frac{1}{1-\sigma}}, \tag{6}$$

[14]The revenue sharing extension in Section 7.1 also explicitly represents competition in the platform service market.

[15]The calibrated model also assumes joint pricing. Our focus is on the growth effects of platform acquisitions rather than static distortions, so we focus on constant markups here for tractability. Quantitatively, we find that the welfare costs of acquisitions for growth are larger than the costs due to markups (Table 4).

by substituting qualities (5) into the price index (4). The price index has three components. Two of them, markups and the love of variety, are standard. The third is new: the platform's technology γ, ecosystem dominance ι_t, tying δ_t, and the household's platform time use $L_{P,t}$ all affect the price of real consumption. All else equal, the price of real consumption falls when

i. the household spends more time using the platform $\left(\frac{\partial P_t}{\partial L_{P,t}} < 0\right)$,

ii. the platform reduces tying $\left(\frac{\partial P_t}{\partial \delta_t} > 0\right)$,

iii. more products are in the platform's ecosystem $\left(\frac{\partial P_t}{\partial \iota_t} < 0 \text{ when } \delta_t > 0\right)$.

Point (iii) says that statically, acquisitions benefit consumers through quality synergies.

Before explaining the determination of equilibrium platform time use, ecosystem dominance, and tying, it is helpful to solve for the firms' profits given these variables. We will focus on balanced growth paths (BGPs) where the entry rate is constant so that N_t grows at a constant rate. On such a BGP the earnings of all firms decrease exponentially because the number of varieties is growing. We characterize the profits at time t as $\frac{\pi_{S,t}}{N_t}$ for the startups and $\frac{\pi_{P,t}}{N_t}$ for each platform product. On a balanced growth path, $\pi_{S,t}$ and $\pi_{P,t}$ are constant. We refer to these as the (detrended) profits:

$$\pi_{p,t} = \frac{1}{\sigma} \frac{1 + \gamma L_{P,t}}{1 + \gamma L_{P,t}(\iota_t + (1 - \iota_t)(1 - \delta_t))}, \tag{7}$$

$$\pi_{s,t} = \frac{1}{\sigma} \frac{1 + \gamma L_{P,t}(1 - \delta_t)}{1 + \gamma L_{P,t}(\iota_t + (1 - \iota_t)(1 - \delta_t))}. \tag{8}$$

In (7) and (8), $\frac{1}{\sigma}$ is the profit margin because all firms charge a constant markup $\frac{\sigma}{\sigma-1}$. In a standard Romer (1990) model, total profits for all firms are also $\frac{1}{\sigma}$ because all firms have one unit of revenue. In the present model, however, the platform introduces dispersion between its own profits and those of startups by using tying to change revenues. We later show tying $\delta_t > 0$ for any level of ecosystem dominance, so that $\pi_{P,t} > \frac{1}{\sigma} > \pi_{S,t}$. Thus, by lowering the perceived quality of startup products, the platform gains an advantage for its own products. This strategic incentive introduces novel implications for growth, as we show later.

Platform Time Use. The household takes tying and prices as given and chooses how much time to spend using the platform.[16] The household faces a trade-off between leisure time and higher real consumption when choosing L_P. The optimal choice equates the marginal benefit and marginal cost of using the platform. The household's problem can be written

$$L_{P,t} = \arg\max_{L_P} \log C_t - L_P = \arg\max_{L_P} -\log P_t - L_P, \tag{9}$$

s.t.

equation (6).

The solution is

$$L_{P,t} = \max\left\{\frac{1}{\sigma-1} - \frac{1}{\gamma(\iota_t + (1-\iota_t)(1-\delta_t))}, 0\right\}. \tag{10}$$

The key result is that the households' platform time use is decreasing in the platform's tying δ_t as long as ecosystem dominance is less than one, but is less sensitive to tying the higher is ecosystem dominance.

Tying. The platform chooses tying to maximize profits (7) taking into account the effect of tying on household platform use (10).[17] This introduces the key tradeoff: tying increases the relative attractiveness of the platform's own products compared to startups, but reduces household platform use, thereby depressing demand for all goods through the platform, including the products operated by the platform itself. The optimal tying choice is

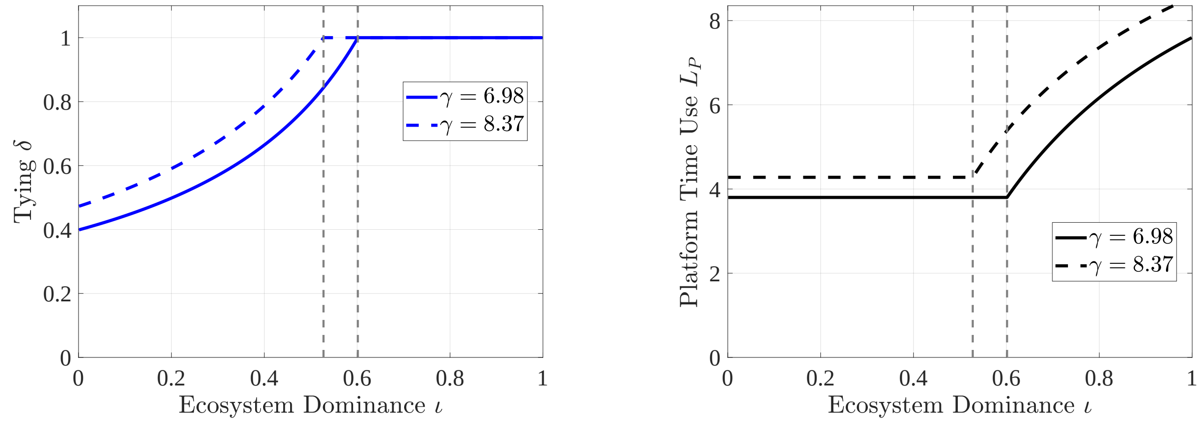
$$\delta_t = \min\left\{\frac{\gamma-(\sigma-1)}{\gamma+(\sigma-1)}\frac{1}{(1-\iota_t)}, 1\right\}. \tag{11}$$

The solution is plotted in Figure 1a. Tying increases in the platform's ecosystem dominance ι_t and in the platform technology γ, until it reaches one (full tying). Tying is positive even when the platform sells a very small share of products ($\iota_t = 0$) because the effect of discouraging platform use in (10) is zero when $\delta = 0$.[18] As the platform

[16] The representative household stands in for many individual households so this assumption is reasonable. The representative household assumption abstracts from positive externalities of platform use across households that are an additional source of platform under-utilization, but that is not the focus of this paper.

[17] The assumption that the tying decision is without attention to the acquisition market is without loss of generality, given our assumption about Nash bargaining over the merger surplus.

[18] At that point, the startups' products and the platform products are identical, so any change in platform time use will not affect the platform's profits directly. Any lost profit from platform products will be directly compensated by reallocated market shares from competitors.



(a) Tying

(b) Platform Time Use

Figure 1: Ecosystem Dominance: Effects on Tying and Household Platform Time Use

Note: Platform tying and household platform use as functions of the platform's ecosystem dominance for the baseline platform technology γ (solid lines) and a γ that is 20% higher (dashed lines). Vertical lines indicate the level of ecosystem dominance where maximal tying is reached. Parameters in Table 2.

approaches full ecosystem dominance ($\iota_t \to 1$), platform use no longer responds to tying since the platform de facto owns all products; this leads to full tying in this limit. It is possible to reach full tying for interior values of ecosystem dominance, and full tying is reached faster when the platform technology γ is better.

Equilibrium platform time use is plotted in Figure 1b. When tying is less than one, an increase in ecosystem dominance has two competing effects on platform time use that are exactly offsetting: first, holding tying fixed, greater ecosystem dominance would have the direct effect of incentivizing households to use the platform more. However, the platform uses this opportunity to increase tying enough to exactly offset the direct effect, keeping equilibrium platform time use unchanged. For interior tying ($\delta < 1$), equilibrium platform use is

$$L_P = \frac{1}{2}\left(\frac{1}{\sigma - 1} - \frac{1}{\gamma}\right). \tag{12}$$

Once maximal tying is reached, the tying effect isn't present anymore and households' platform time use begins to increase in ecosystem dominance.

Comparing the solid and dashed lines in Figure 1b, which represent different values of the platform technology γ, gives a sense of how we identify γ in the calibration. Conditional on the elasticity of substitution, equation (12) provides a direct mapping from data on platform time use to the platform technology parameter γ: more plat-

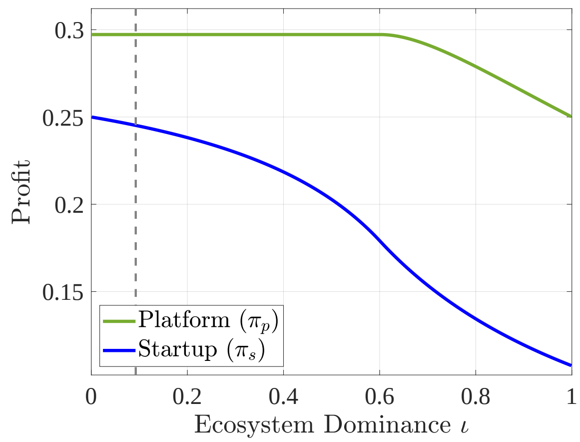


Figure 2: Startup Profits Decline in Ecosystem Dominance

Note: Startup profits (blue) and platform profits (green) as functions of the platform's ecosystem dominance using the parameters in Table 2. Vertical line is the calibrated value of ecosystem dominance (Section 6).

form time use suggests the platform technology is better.

Finally, given equilibrium tying and platform use, Figure 2 shows firm profits (equations (7) and (8)). Startup profits fall as ecosystem dominance rises because time use is fixed and tying is increasing in ecosystem dominance (for interior tying).[19]

Dynamic Equilibrium. The entry rate (equivalently the growth rate g_t) depends both on the forward-looking value of a startup and the forward-looking value of a platform product because the latter determines the surplus created from acquisitions. We denote the detrended value of a platform product line as v_{Pt} and that of a startup as v_{St}. In other words, the value of these firms at t is $\frac{v_{Pt}}{N_t}$ and $\frac{v_{St}}{N_t}$, where

$$(g_t + \rho)\, v_{Pt} = \pi_s(\iota_t) + \dot{v}_{Pt}, \tag{13}$$

and

$$(g_t + \rho)\, v_{St} = \underbrace{\pi_s(\iota_t)}_{\text{Profits}} + \underbrace{\mu\beta\,(v_{Pt} - v_{St})}_{\text{Option Value of Acquisition}} + \dot{v}_{St}. \tag{14}$$

The derivations are in Appendix B.2. The platform and startups have the same discount rate $g_t + \rho$. Their values differ in two regards: the platform has weakly higher flow profits (strictly higher when tying is positive); the startups additionally receive

[19]Platform profits per product line start to fall once maximal tying is reached because platform products begin to cannibalize each other.

the *option value of acquisition*. The startup meets the platform for acquisition at rate μ. In these events, the startup receives a share β of the surplus $v_{Pt} - v_{St}$.

Positive entry requires that new startups must be indifferent about whether to enter, that is, $\kappa(g_t) = v_{St}$. Combining this with the value function yields the free-entry condition which must hold for any instant t:

$$(g_t + \rho)\kappa(g_t) = \pi_s(\iota_t) + \mu\beta\left(v_{Pt} - \kappa(g_t)\right) + \kappa'(g_t)\,\dot{g}_t. \tag{15}$$

Integrating equation (13) gives the value of a platform product for any path of growth rates. We thus treat v_{Pt} as a known function from here on. From the free entry condition, we can derive the equilibrium growth rate.

Ecosystem dominance changes over time according to the following law of motion:

$$\dot{\iota}_t = \mu - (g_t + \mu)\iota_t. \tag{16}$$

Given a fixed growth rate, a higher acquisition rate μ increases the ecosystem dominance of the platform. Given a fixed acquisition rate, a higher startup rate g_t decreases the ecosystem dominance of the platform. Our definition of a dynamic equilibrium thus involves two equations for $\{\iota_t, g_t\}$.

Definition 1. *A dynamic equilibrium is a combination of two functions $\{\iota_t, g_t\}$ such that equation (15) and equation (16) hold.*

Other Equilibrium Objects. There are two other equilibrium objects that are welfare-relevant. These can be written as analytical functions given a dynamic equilibrium. We summarize these objects in the following lemma.

Lemma 1. *Given $\{\iota_t, g_t\}$:*
(Real consumption)

$$C_t = \underbrace{\frac{\sigma}{\sigma-1}}_{\textit{markup}} \times \left(\underbrace{N_0 e^{\int_0^t g_s ds}}_{\textit{love of variety}} \times \underbrace{\left(1 + \gamma L_{P,t}(\iota_t + (1-\iota_t)(1-\delta_t))\right)}_{\textit{platform}}\right)^{\frac{1}{1-\sigma}}.$$

(Labor)

$$L_t = \int_0^{N_t} c_{i,t}\,di + \kappa(g_t)g_t + L_{P,t}. \tag{17}$$

Equation (17) tallies the total labor supplied to production, creation of new firms, and platform time use. Total entry costs are $\kappa(g_t) \times g_t$ (the per-entrant cost is $\frac{\kappa(g_t)}{N_t}$).

3.3 Special Case: Balanced Growth Path

On a balanced growth path, the growth rate and the platform's ecosystem dominance are both constants, denoted as g^* and ι^*. Given ecosystem dominance ι^*, the BGP growth rate must be consistent with the free-entry condition of the startups:

$$(g^* + \rho)\,\kappa(g^*) = \pi_s(\iota^*) + \mu\beta\left(\frac{\pi_p(\iota^*)}{g^* + \rho} - \kappa(g^*)\right).$$

Given the growth rate, ecosystem dominance must also stay constant:

$$\iota^* = \frac{\mu}{\mu + g^*}.$$

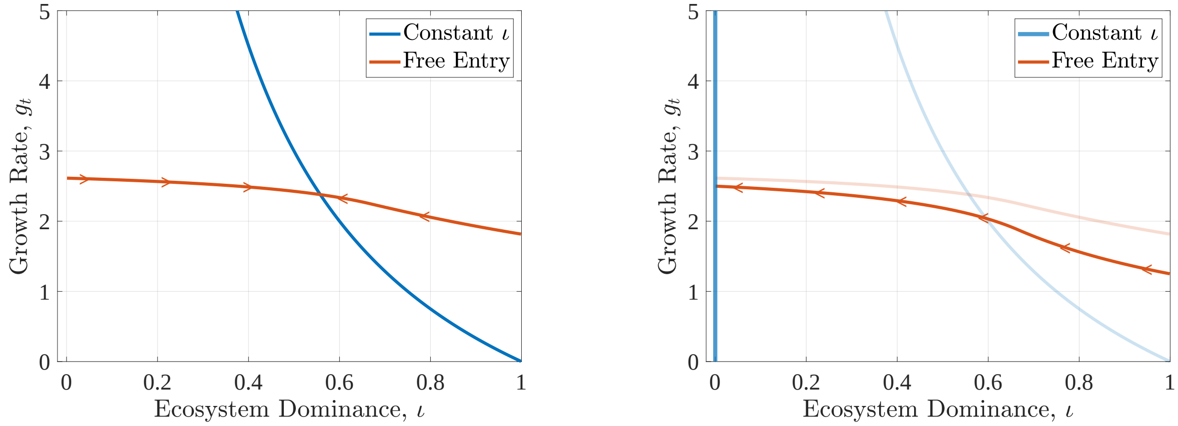
The balanced growth path equilibrium can be analyzed on a 2-dimensional plane of g^* and ι^*, depicted in Figure 3a. The free-entry condition imposes a downward-sloping relationship between ecosystem dominance and growth rate: higher ecosystem dominance leads to more tying and lower profits for the startups, which discourages entry; the steady-state condition for ecosystem dominance requires another downward-sloping relationship between ecosystem dominance and the growth rate: a lower growth rate leads to more ecosystem dominance. The equilibrium pair (g^*, ι^*) is the intersection of these two curves.

4 Effect of An Acquisition Ban on Growth

We now return to the central question of the paper: what happens to the economy's growth rate if policymakers regulate platform acquisitions more strictly? This section considers the case of a total acquisition ban, and Appendix B.5 derives similar results for small, local changes in the acquisition rate.

The model is simple enough to analytically characterize the path of the economy's growth rate over the transition from a balanced growth path with acquisitions to one without acquisitions if we make a standard assumption about the form of entry costs (Romer 1990). The assumption needed is that the entry cost is constant: $\kappa(g) = \kappa$, that is, $\eta = 0$.

Suppose the economy is on a balanced growth path with $\mu > 0$ and equilibrium $(g_o^*, \iota_o^*,$. At time 0, the government bans platform acquisitions, setting the acquisition rate $\mu = 0$. Given this policy, the platform's ecosystem dominance monotonically decays at rate g_t starting from the "old" ecosystem dominance $\iota_0 = \iota_o^*$ following equation (16). The transition path of ecosystem dominance is $\iota_t = \iota_o^* e^{-\int_0^t g_s ds}$.



(a) BGP with Acquisitions

(b) BGP with No Acquisitions

Figure 3: Impact of An Acquisition Ban on Model Steady State

Note: The x-axis plots ecosystem dominance, and the y-axis plots the growth rate. The blue curve plots the combinations of (ι, g) such that $\dot{\iota} = 0$, and the red curve plots the combination of (ι, g) such that the free-entry condition holds. Panel (a) sets the acquisition meeting rate to be $\mu = 0.03$ and panel (b) sets $\mu = 0$. The arrows point in the direction of convergence towards the new balanced growth path. Other parameters are set as: $\rho = 0.02$, $\gamma = 4$, $\beta = 0.5$, $\sigma = 4$, $\kappa = 10$.

Startups' option value of acquisition becomes zero due to the policy (eq. 14). A startup's value v_{St} then comes only from operating profits $\pi_s(\iota_t)$. The growth rate on the transition path thus equates the entry cost to the operating value, for any t:

$$(\rho + g_t)\,\kappa = \pi_s\left(\iota_o^* e^{-\int_0^t g_s ds}\right). \tag{18}$$

Lemma 2 (Acquisition Ban: Transition Path)**.** *Assume $\kappa(g) = \kappa$ and constant markups. On the transition path from a BGP with $\mu > 0$ towards a BGP with no acquisitions ($\mu = 0$): $g_0 < g_o^*$ and $\frac{dg_t}{dt} > 0$, where g_0 is the time 0 growth rate on the transition path and g_o^* is the old BGP growth rate with acquisitions.*

The proof is in Appendix B.3. Lemma 2 provides two results about the transition path of the growth rate after an acquisition ban. First, growth immediately falls compared to the old steady state when the ban is implemented ($g_0 < g_o^*$). This is intuitive: ecosystem dominance (and thus startup profits) are unchanged but the option value of acquisition is gone. Second, the growth rate is increasing over the transition to the new steady state. This is also intuitive, since startup profits increase as the platform's ecosystem dominance declines over time, creating stronger incentives to enter.

Figure 3 depicts the intuition graphically: from the initial steady state with acquisitions in panel 3a, the acquisition ban equilibrium (panel 3b) differs in two ways. First, the free entry curve immediately shifts down due to the lost option value of acquisition. The initial growth rate on the transition path g_0 is the intersection of ι_o^* and the new free entry curve, so below g_o^*. Then the economy moves along the free entry curve with growth increasing from g_0 towards the new steady state, which is the intersection of the new free entry curve and the new constant ecosystem dominance curve (any g is consistent with constant ecosystem dominance when μ is 0 so this line is vertical). Figure 4 plots the time paths of the growth rate and ecosystem dominance. Notice that in this example, the acquisition ban increases the growth rate in the long run. Lemma 3 derives a condition for this to be the case.

Lemma 3 (Acquisition Ban in the Long Run)**.** *Assume $\kappa(g) = \kappa$ and constant markups. If the equilibrium with acquisitions has interior tying, an acquisition ban increases the BGP growth rate if and only if*

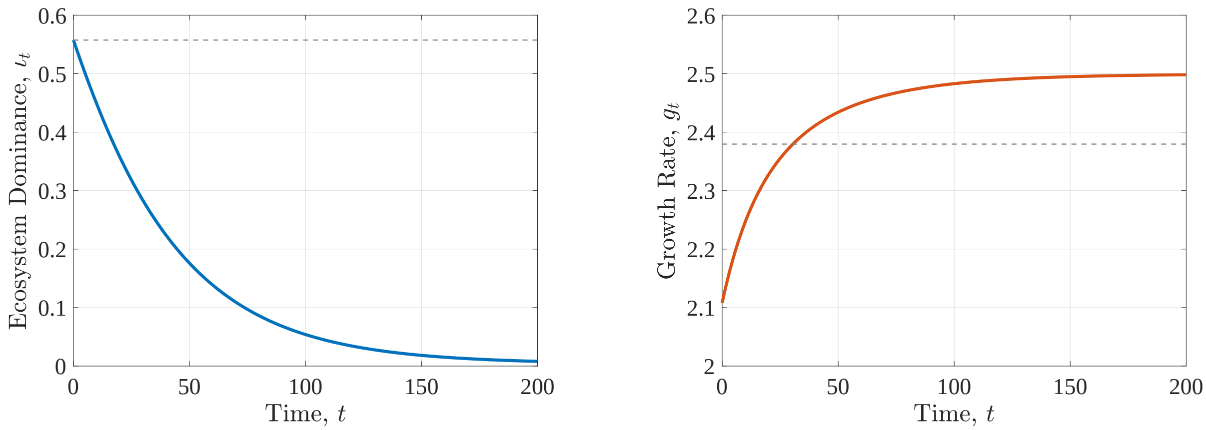
$$\underbrace{\beta\left(\frac{\pi_{p,o}^*}{\kappa(\rho+g_o^*)}-1\right)}_{M\ \&A\ Premium} < \frac{1}{\mu\kappa}\underbrace{\left(\frac{1}{\sigma}-\pi_{s,o}^*\right)}_{Wedge\ in\ Profits}.$$

The proof is in Appendix B.4. Lemma 3 links the effect of an acquisition ban on the long run growth rate to several objects, potentially measurable in the data.[20] The first is the "M&A Premium" which is the value paid by the platform to acquire the startup over and above the pre-acquisition value of the startup.[21] The premium is given by the total surplus created from the difference in profitability of the platform and startups times the entrant bargaining power β which governs the share of surplus going to the target.[22] All else equal, if the premium is low, an acquisition ban is more likely to increase growth because the option value of acquisition is not a major motive for entry in the initial equilibrium.

[20] The challenge with measuring these objects in the data is the lack of pre-acquisition valuations and other financial information for target firms, since only six out of the hundreds of targets in our sample were public at the time of acquisition. The calibration uses indirect inference to estimate the parameters and checks whether the condition holds.

[21] Table A.1 reports the premium for deals where the target was public prior to acquisition. Platforms' average premium was 83%, higher than the 46% average of other large firms, but this is based on only six deals: Google's acquisitions of Fitbit (143%), Motorola (84%), Global IP Solutions (26%), On2 Technologies (95%); Apple's acquisition of AuthenTec Inc (85%); Amazon's acquisition of Whole Foods Market (45%).

[22] Kamepalli, Rajan, and Zingales (2020) argue that startup bargaining power against platforms in acquisitions may be low relative to traditional industries because of the threat of exclusion from the platform.



(a) Ecosystem Dominance

(b) Growth Rate

Figure 4: Transition Path After An Acquisition Ban

Note: The x-axis plots time, and the y-axis plots the ecosystem dominance (panel a) and the growth rate (panel b) on the transition path towards a balanced growth path (BGP) without acquisitions. The dashed lines indicate the old BGP values of the variables. The same set of parameters as in Figure 3 are used.

The other case where this condition is likely to hold is when the platform technology γ is very good. When γ is high, the wedge between startups' standalone profits $\pi^*_{s,o}$ and the usual profit margin $\frac{1}{\sigma}$ is larger through two channels. The first is a direct effect: equation (8) shows that for given ecosystem dominance and tying, startup profits are lower when γ is higher. Second, the platform strategically chooses higher tying when γ is high (Figure 1a.) Taken together, this means that the change in startups' profits due to an acquisition ban will be larger when γ is higher.

5 Welfare

Turning to normative implications, we first decompose welfare in this economy on any balanced growth path into terms that have natural interpretations. Then we solve for the efficient allocation to highlight various distortions in the competitive equilibrium. The final part of this section returns to the question of an acquisition ban.

5.1 Welfare Decomposition on A Balanced Growth Path

The model lends itself to a linear decomposition of the household's welfare on a balanced growth path. We start by introducing an alternative price index that isolates the role of the platform. Given platform time use L_P, tying δ, and ecosystem dominance ι, we define this utilization index as:

$$P^u \equiv (1 + \gamma L_P(\iota + (1-\iota)(1-\delta)))^{\frac{1}{1-\sigma}}\,.$$

P^u is the price index for the household if there is a unit mass of varieties and all firms charge their marginal cost of production. It captures the pure effect of platform use.

Secondly, we define a measure of aggregate labor productivity in this economy:

$$Z \equiv \frac{\left(\iota\, p_P^{1-\sigma}(1+\gamma L_P) + (1-\iota)\, p_S^{1-\sigma}(1+\gamma L_P(1-\delta))\right)^{-\frac{\sigma}{1-\sigma}}}{\iota\, p_P^{-\sigma}(1+\gamma L_P) + (1-\iota)\, p_S^{-\sigma}(1+\gamma L_P(1-\delta))}, \tag{19}$$

where p_S is the price charged by the startups and p_P is the price charged by the platform. With this definition, $C_t = Z L_Y N_t^{\frac{1}{\sigma-1}}$. Thus Z measures how much additional real consumption can be created when production labor increases. In the baseline model, the markups are the same for platform goods and startups and labor productivity equals the inverse of the utilization index: $Z = 1/P^u$.

The discounted utility W of the household on a balanced growth path can then be decomposed into six components,

$$W = \underbrace{\frac{g}{\rho^2(\sigma-1)}}_{\text{Growth}} + \frac{1}{\rho}\left(- \underbrace{\log P^u}_{\text{Utilization}} - \underbrace{\log \frac{P}{P^u}}_{\text{Markup}} - \underbrace{\frac{1}{PZ}}_{\text{Production Cost}} - \underbrace{\kappa(g) g}_{\text{Entry Cost}} - \underbrace{L_P}_{\text{Utilization Cost}} \right). \tag{20}$$

The first term captures the effect of growth in terms of new varieties. The rest of the terms capture the welfare effects of static allocations. The first static component is the utilization of the platform service assuming firms do not charge any markup. The second term captures the consumption impact of the average markup, measured as the gap between the equilibrium price index and the utilization index. The final static welfare components are the labor costs associated with different activities.[23]

[23] In the decomposition of welfare changes between BGPs in the quantitative analysis we call the contribution of "Growth" the change in the growth term net of changes in entry costs, "Platform" the change in the utilization term net of changes in platform time use (utilization costs), and "Markup" the change in the markup term net of changes in production costs.

5.2 Efficient Allocation

The planner maximizes the discounted utility of the household, subject to the resource constraints:

$$W^{SP} = \max_{c_{it}, L_t, \dot{N}_t} \int_0^\infty e^{-\rho t} \left[\log C_t - L_t\right] dt, \tag{21}$$

s.t.

Equation (2), (16), (17),

with ι_0 given. To characterize the planner's solution, we first simplify her constraints. To the planner, the tying decision is irrelevant because it is always beneficial to fully share the platform technology across all products. Thus $\delta_t = 0$. Since all products then have the same quality, the planner chooses equal consumption of all products. The resulting labor productivity is $Z_t = (1 + \gamma L_{P,t})^{\frac{1}{\sigma-1}}$ and aggregate consumption is $C_t = Z_t L_{Y,t} N_t^{\frac{1}{\sigma-1}}$. With these simplifications, the planner's value can be written

$$\rho W^{SP}(N) = \max_{L_P, L_Y, \dot{N}} \log\left((1+\gamma L_P)N\right)^{\frac{1}{\sigma-1}} L_Y - \left(L_P + L_Y + \kappa\left(\frac{\dot{N}}{N}\right)\frac{\dot{N}}{N}\right) + \dot{N} W^{SP\prime}(N).$$

In her optimal allocation, the social planner equalizes the societal value of additional production labor to the household's disutility of working. Thus, $L_Y^{SP} = 1$. Similar logic implies that the optimal platform time use is

$$L_P^{SP} = \frac{1}{\sigma - 1} - \frac{1}{\gamma}. \tag{22}$$

We show in Appendix B.6 that the optimal growth rate g^{SP} is summarized by the following differential equation:

$$\rho\left(\kappa'\left(g^{SP}\right) g^{SP} + \kappa\left(g^{SP}\right)\right) = \frac{1}{\sigma - 1} + \left(\kappa''\left(g^{SP}\right) g^{SP} + \kappa'\left(g^{SP}\right)\right) \dot{g}^{SP}. \tag{23}$$

Distortions. Comparing platform time use in equations (12) and (22), it is clear that tying results in under-utilization of the platform by households in the competitive equilibrium. Tying not only affects the static allocation but also impacts the growth rate; contrasting the free entry condition (15) to the planner's optimality condition for the growth rate (23) reveals that in the efficient allocation the platform's service is growth-neutral, whereas in the competitive equilibrium tying lowers startup profits ($\pi_s(\iota) < \frac{1}{\sigma-1}$) and distorts the entry rate.[24]

The other distortions to the growth rate are standard in this class of models. First, the planner and the entering firms face different effective discount rates. The planner's discount rate aligns with the household, ρ; the entering firms' discount rate is $\rho + g$ because a higher growth rate leads to a faster reduction in individual firms' profits. Second, the social return of an additional firm is $\frac{1}{\sigma-1} > \frac{1}{\sigma}$ because knowledge spillovers lower entry costs for future startups. Third, there is a congestion externality on current period entry when $\eta > 0$ (Klenow and Li 2025). There is a final standard static distortion that markups depress production labor: $L_Y = \frac{\sigma-1}{\sigma} < 1$.

5.3 Welfare Effects of An Acquisition Ban

The (possible) growth benefit of an acquisition ban occurs in the long run while the costs are incurred in the short run. We again highlight this tradeoff by considering the welfare effect of an acquisition ban under constant markups and constant entry costs.

Lemma 4. *Assume constant markups and $\kappa(g) = \kappa$. If the equilibrium with acquisitions has interior tying, the discounted welfare impact of an acquisition ban is the discounted gap between growth rate paths:*

$$\Delta W = \left(\frac{1}{\sigma-1} - \rho\kappa\right) \int_0^\infty e^{-\rho t}(g_t - g_o^*)dt. \tag{24}$$

The proof is in Appendix B.7. With constant markups, there is no change in the markup component of (20) due to the ban. The platform component P^u is also unchanged because the ban results in lower ecosystem dominance but this causes lower tying (equation (11)) that exactly offsets the change in ecosystem dominance. The decision about whether or not to ban acquisitions can therefore be taken in two steps: first evaluate whether a ban increases the long run growth rate. If not, the policy is unambiguously bad. If it is, then the policymaker must trade off the cost of initially lower growth against higher long run growth using the appropriate household discount rate ρ. The calibration is such that the pre-platform growth rate is positive; this requires $\frac{1}{\sigma} > \rho\kappa$. This implies that $\frac{1}{(\sigma-1)} - \rho\kappa > 0$. Thus, an acquisition ban increases

[24] If $\beta = 1$ and $\mu \to \infty$ in the competitive equilibrium, the platform service becomes growth-neutral because startups are acquired immediately and capture the full surplus created by the acquisition, equalizing the platform and startup firm values.

welfare if and only if the discounted growth rate in the transition is larger than the discounted growth rate on the old BGP.

6 Quantitative Model

This section extends the model to include variable markups to bring the quantitative model closer to the data. We then calibrate this extended model, explore the short and long run effects of competition policy (both acquisition and tying regulation), and discuss the sensitivity of the policy conclusions to parameter choices.

6.1 Variable Markups

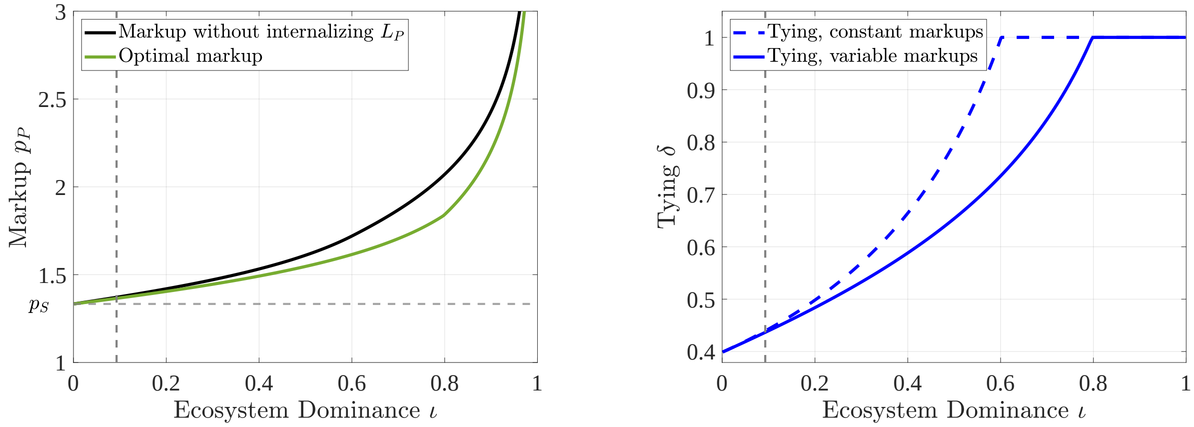
The baseline model assumed that the platform ignored its effect on the aggregate price index when choosing prices for its products. Relaxing this assumption yields a symmetric problem for the platform across all of its products:

$$\begin{aligned}
\max_{p_P,\delta\in[0,1]} \quad & \pi_P = (p_P - 1)\left(1 + L_P\gamma\right)\left(\frac{p_P}{P}\right)^{-\sigma} P^{-1} \\
\text{s.t.} \quad & L_P = \left(\frac{1}{\sigma-1} - \frac{1}{\gamma}\frac{\iota p_P^{1-\sigma} + (1-\iota)p_S^{1-\sigma}}{\iota p_P^{1-\sigma} + (1-\iota)\left(1-\delta\right)p_S^{1-\sigma}}\right) \\
\text{and} \quad & P = N^{\frac{1}{1-\sigma}}\left(\iota(1+L_P\gamma)p_P^{1-\sigma} + (1-\iota)(1+L_P\gamma\left(1-\delta\right))p_S^{1-\sigma}\right)^{\frac{1}{1-\sigma}}.
\end{aligned} \tag{25}$$

Note that L_P is decreasing in the platform's price. Appendix B.8 derives the first order conditions of the problem. The solution for the price is

$$p_P = \frac{\sigma - (\sigma-1)\tilde{s}_P}{(\sigma-1)(1-\tilde{s}_P)} \quad \text{where } \tilde{s}_P = s_P\left(1 - \frac{\frac{\partial L_P}{\partial p_P}}{\frac{\partial L_P}{\partial \delta}}\right).$$

This is the standard solution where the markup increases in the market share, except that the relevant market share $\tilde{s}_P$ is less than the actual market share s_P because $\frac{\partial L_P}{\partial p_P}$ and $\frac{\partial L_P}{\partial \delta}$ are negative. This downward adjustment to the markup due to endogenous platform use is small in the calibrated model, especially for low levels of ecosystem dominance (Figure 5a). When the platform can adjust prices as well as tying, desired tying is lower for the same level of ecosystem dominance, though for low values of ι this difference is also small (Figure 5b).



(a) Variable Markups

(b) Tying with Variable Markups

Figure 5: Platform's Markup and Tying

Note: Panel (a) compares the standard pricing solution with CES demand and granular market shares (Atkeson and Burstein 2008) to the platform's markup in our model with endogenous platform time use. The dashed line is the startups' markup. Panel (b) compares platform tying in the version of the model with constant markups to platform tying with variable markups. Parameters in Table 2.

6.2 Calibration

The calibration proceeds in several steps. First, standard values for household preferences are taken from the literature, with $\rho = 0.02$ (for an annual real interest rate of 2%) and $\sigma = 4$ (this implies firm-level markups for startups of 33%, in line with the estimates of De Loecker, Eeckhout, and Unger (2020) and De Ridder, Grassi, and Morzenti (2024) and the love-of-variety estimate in Baqaee et al. (2025)). We set the target's (startup's) bargaining power $\beta = 0.5$ as estimated by David (2020) but explore sensitivity of the results to this choice since the option value of acquisition is a key force in the model. Finally, we follow Acemoglu et al. (2018) in setting $\eta = 1$.

Second, we compute a "pre-platform" steady state of the model to calibrate the entry cost κ. In this steady state $\gamma = 0$ so that there is no technological benefit of the platform. Growth in this steady state is driven purely by the balance between startup profits and entry costs. We pick κ to match an annual growth rate of 2%, roughly the average annual growth rate in the U.S. prior to the advent of digital platforms.

Third, we compute a "platform" steady state to calibrate the platform technology parameter γ. The model measure of time spent on the platform is L_P. We take the data analog of this moment to be time spent online from Nielsen's (2021) by U.S. households. U.S. households spent 3.8 hours per day online across computers, smartphones

	Value	Meaning	Source/Target
Panel A: Calibrated from Literature			
ρ	0.02	Discount rate (annual)	Standard
σ	4	Elasticity of substitution	De Loecker et al. (2020)
η	1	Entry cost, curvature	Acemoglu et al. (2018)
β	0.5	Entrant bargaining power	David (2020)
Panel B: Calibrated from Data			
κ	52	Entry cost, constant	Growth rate
γ	6.98	Platform technology	Platform time use
μ	0.0061	Merger meeting rate	Platform revenue share

Table 2: Model parameters, baseline.

and tablets in 2021. Given the uncertainty around how much of this time is spent engaging in the sort of activities our model captures, as well as γ's role in governing the response of startup profits to an acquisition ban, we explore the sensitivity of our results to this choice.

The final parameter is the acquisition meeting rate μ. We choose μ to match the revenue share of the platform in the platform steady state. The data target is $\frac{\text{total GAFAM revenues in Compustat}}{\text{total U.S. non-farm, non-financial revenues}} = 11\%$. The calibrated value of μ implies a steady state ecosystem dominance of 9.33 %, that is, the platform supplies roughly 1 out of 10 products in the economy. Tying causes the platform to capture a slightly larger share of total revenue (11%) than its share of products. Table 2 summarizes the calibrated parameters.

Table 3 demonstrates the model fit of the data for the pre-platform and platform economies. The model is capable of matching platform time use and the platform's revenue share exactly. The parameter choices imply tying of 44%, meaning 56% of the platform's appeal is shared with third party sellers. The middle panel reports the steady state welfare gain (1.5%) associated with the introduction of the platform into the economy. Households generate significant real consumption benefits by using the platform. These benefits are large enough to outweigh the slight decline in the growth rate due to tying and a slight increase in the markup distortion. The bottom panel reports the *discounted* welfare gains from the point of view of the pre-platform equilibrium over the transition to the platform steady state, which are 1.6%. The bene-

	Data	Pre-platform	Platform
Panel A: Model Fit for Targeted Moments			
Growth rate, %	2.000	2.003	1.999
Platform time use, hours/day	3.8	0	3.8
Platform revenue share, %	11	0	11
Tying δ, %	-	0	44
Panel B: Steady State Welfare Comparison			
BGP Welfare, CE % chg.	-	-	1.5
Growth	-	-	-0.2
Platform	-	-	1.7
Markup	-	-	-0.1
Panel C: Welfare Over the Transition			
Transitional Welfare, CE % chg.	-	-	1.6

Table 3: Top panel: Model fit for targeted moments given the parameterization in Table 2. Middle panel compares steady state welfare between the pre-platform steady state and the platform steady state. Bottom panel shows the discounted welfare over the transition from the pre-platform steady state to the platform steady state. CE = consumption equivalent. See section 5.1 for more details on welfare components.

fits of platform use occur immediately while the costs from higher markups and tying take time to kick in as ecosystem dominance builds up over time.

6.3 Policy Experiments

Table 4 summarizes the results of two policy experiments: an acquisition ban and a tying ban. These experiments are conducted starting from the platform steady state.

Acquisition Ban. An acquisition ban restores the higher growth and lower markups of the pre-platform equilibrium by reducing ecosystem dominance to zero, thereby reducing tying, without changing platform utilization much.[25] But these welfare gains are so small that the discounted welfare effect over the transition is near zero; the

[25]Recall that tying does not converge to zero as ecosystem dominance converges to zero.

	Base.	Acq. Ban	Tying Ban	First Best
Panel A: Model Fit for Targeted Moments				
Growth rate, %	1.999	2.003	2.010	5.349
Platform time use, hours/day	3.8	3.8	7.6	7.6
Platform revenue share, %	11	0	9	4
Tying δ, %	44	40	0	0
Panel B: Steady State Welfare Comparison				
BGP Welfare, CE % chg.	-	0.18	7.79	63.72
Growth	-	0.15	0.37	52.47
Platform	-	-0.04	7.41	7.41
Markup	-	0.07	0.01	3.84
Panel C: Welfare Over the Transition				
Transitional Welfare, CE % chg.	-	0.08	7.79	63.54

Table 4: Features of model steady state with no policy interventions (”Base.”), a policy blocking nearly all acquisitions ($\mu \approx 0$), or a policy banning tying ($\delta = 0$), compared to the first best. CE = consumption equivalent. See section 5.1 for more details on welfare components.

consumption equivalent welfare gain is 0.08%.[26] The sensitivity analysis in the next section reveals that small and reasonable parameter changes can turn the predicted welfare effects of an acquisition ban negative.

Tying Ban. By contrast, a tying ban provides potentially large and immediate welfare benefits. It eliminates differences in profits for the platform and standalone firms, which increases the long run growth rate even more than an acquisition ban. The bulk of the gains, however, come from eliminating platform under-utilization. Using the platform now generates higher quality across all products in the economy equally. Households devote twice as much time to using the platform, resulting in substantially higher utility from consumption each period. The markup gains, which are smaller than in the acquisition ban case because the platform maintains a non-negligible market share, occur because the faster growth rate of new firms erodes the platform’s market share compared to the baseline economy.

[26]The difference between welfare over the transition and steady state welfare highlights the importance of the discount rate in assessing the effects of the policies (Caplin and Leahy 2004; Cropper et al. 2014).

It's not exactly clear how to detect and regulate tying in practice, and this is perhaps why regulators have mostly focused on acquisitions. However, Waldfogel (2024) finds that Europe's Digital Markets Act, which prohibited self-preferencing in search, reduced Amazon's self-preferencing from 30 ranks to 20; not a complete elimination of tying, but demonstrating that this sort of regulation affects platform behavior.

6.4 Sensitivity Analysis for Acquisition Ban Results

Finally, Lemma 3 showed that the long-run growth effects of an acquisition ban depend on the relative strength of changes in the option value of acquisition and the elasticity of startup profits to changes in ecosystem dominance. Intuitively, the entrant's bargaining power β determines the size of the option value of the acquisition, and the platform technology parameter γ controls how startup profits respond to ecosystem dominance, so we explore the sensitivity of the results to these two parameters.

Startup Bargaining Power. This exercise varies startup bargaining power β between 0 and 1 with all other parameters held at their baseline values from Table 2 and computes a new competitive equilibrium for each value of β. The top left panel of Figure 6 shows the merger premium (defined in Lemma 3) in the associated steady state and the top right panel shows the discounted welfare change over the transition from that steady state to an acquisition ban equilibrium.

Consistent with Lemma 3, the welfare effects of an acquisition ban are larger when the merger premium is low, and turn negative if the premium is sufficiently high, around $\beta = 0.65$. This is because the option value of acquisition provides a significant entry motive in the pre-ban steady state for high values of startup bargaining power. Note that for all possible values of β the merger premium in the calibrated model is low, at most 20% when startups capture the entire merger surplus, compared to the 47% average premium found by David (2020), who includes all acquisitions of public firms, and our Table A.1 that focuses on the largest acquirers and finds premiums between 45-83% depending on the acquirer type.[27] This suggests that we may be understating the costs of an acquisition ban and thus our baseline results should be interpreted with caution.

[27] The 83% is for platform-based firms but is based on only six observations.

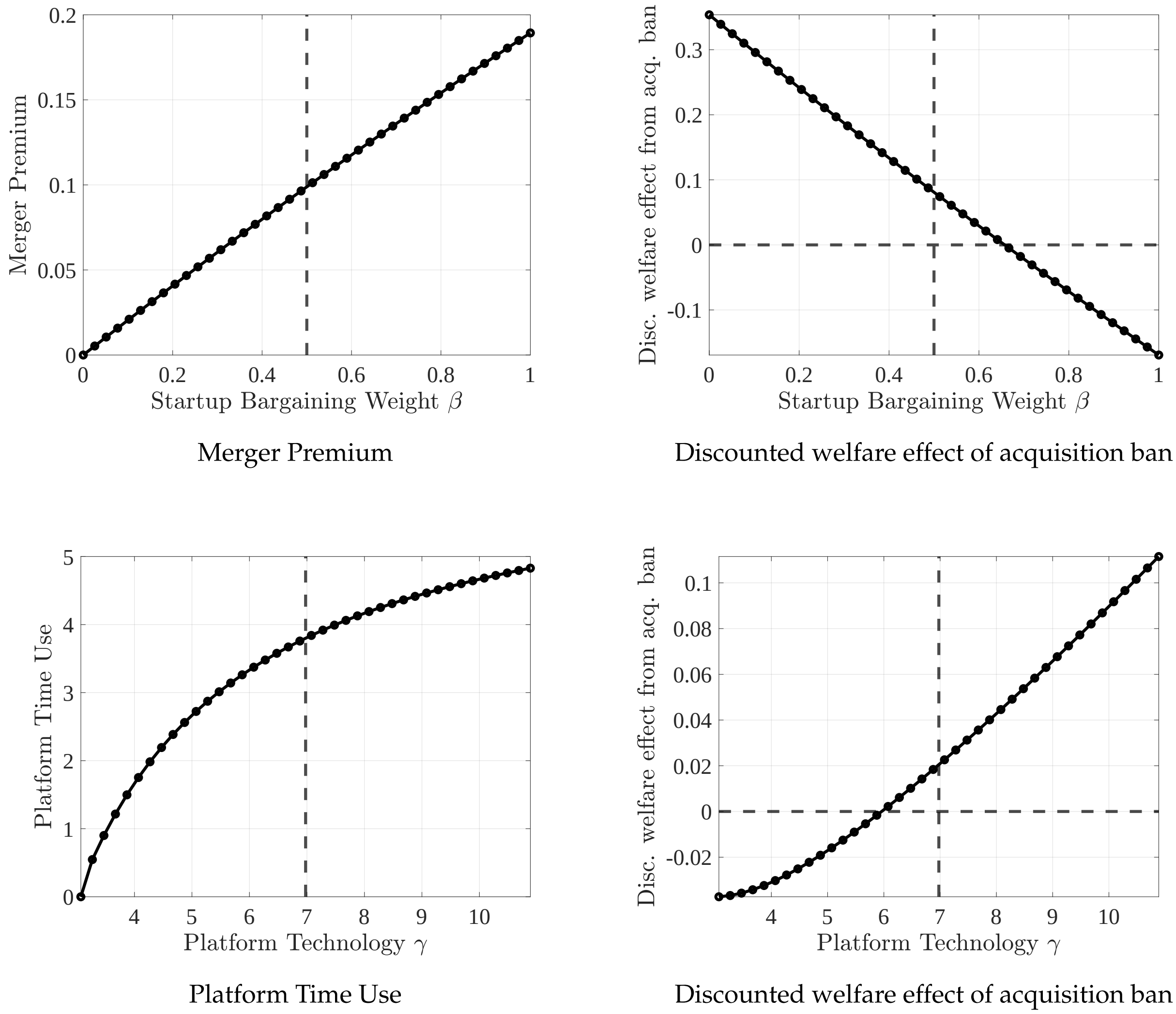


Figure 6: Welfare Effects of An Acquisition Ban Under Alternative Calibrations

Note: Sensitivity analysis of the welfare effects of an acquisition ban to changes in the startup bargaining power β (top panel) and the platform technology γ (bottom panel). The vertical dashed lines indicate the baseline calibrated value of each parameter. Other parameter values in Table 2.

Platform Technology. Alternative targets for platform time use L_P imply different values of the platform technology parameter γ. Varying γ affects the platform's revenue share, so for each value of γ, μ is re-calibrated to match the platform revenue share of 11%. The results are in the bottom panel of Figure 6. When γ is low an acquisition ban lowers welfare because there is not a strong response of startup profits to the ban. For example, a value of platform time use of 8 minutes per day consistent with survey evidence about online shopping time only (SWNS 2024), implies $\gamma = 3.25$ (compared to the baseline value 6.98) and the welfare loss from an acquisition ban is 0.12%.[28] As with entrant bargaining power, reasonable changes to the time use target reverse the policy prescription of the model.

7 Model Extensions

This final section extends the baseline model in two ways. In the first, the platform sells its appeal as a service to startups. The platform's markup on its service creates a similar wedge between platform and startup profits as tying. The second extension adds productivity shocks and operating costs to the baseline model, creating a motive for exit. Tying generates a wedge between the exit threshold of platform products and startups, meaning that platform products have lower productivity on average.

7.1 Revenue Sharing

This extension introduces a market for the platform's appeal, conceptualizing it as a service that can be sold to startups (e.g. sponsored products in search). Instead of choosing tying, the platform indirectly affects the startups' utilization u_i of the platform by choosing a price for its services. The quality of a product is now given by

$$\alpha_i = 1 + \gamma L_P u_i^{\epsilon},$$

where $\epsilon \in (0, 1)$ is the *utilization elasticity* that can be interpreted either as (i) a technology parameter governing the diminishing returns to using the platform service or (ii) a competition parameter between different platforms in the market for providing

[28] This is in spite of the fact that the merger premium rises with γ (see Appendix Figure C.3), which pushes in the opposite direction in terms of welfare through its effect on the option value of acquisition.

platform services.[29] When $\epsilon < 1$, there is a downward-sloping demand curve for the platform's service. The platform's marginal cost of providing a unit of service is ψ.

The profit-maximizing utilization for a startup is given by

$$\max_u \frac{1}{\sigma} \frac{1 + \gamma L_P u^\epsilon}{1 + \gamma L_P \left(\iota u_P^\epsilon + (1-\iota) u_S^\epsilon\right)} - qu.$$

Note that an individual startup takes other startups' utilization, which determines the price index in the denominator, as given. Solving this problem and imposing symmetry ($u = u_S$) implies an inverse demand curve for the platform's service

$$q = \frac{1}{\sigma} \frac{\epsilon \gamma L_P u_S^{\epsilon - 1}}{1 + \gamma L_P \left(\iota u_P^\epsilon + (1-\iota) u_S^\epsilon\right)}. \tag{26}$$

Fixed Platform Time Use. We first solve the platform's optimization problem regarding its service fee q and self-utilization u_P taking as given L_P to highlight the central mechanism:

$$\max_{u_P, q} \iota \pi_P + (1-\iota) q u_S - (\iota u_P + (1-\iota) u_S)\psi,$$

where the first term is the platform's profits from goods sold, the second term is service fees from startups, and the last term is the total cost of providing platform services to itself and to startups. From equation (26), choosing the price q is equivalent to choosing the startups' utilization so the problem can be rewritten as

$$\max_{u_S, u_P} \ \iota \pi_P + (1-\iota) \frac{\epsilon}{\sigma} \frac{\gamma L_P u_S^\epsilon}{1 + \gamma L_P \left(\iota u_P^\epsilon + (1-\iota) u_S^\epsilon\right)} - (\iota u_P + (1-\iota) u_S)\psi. \tag{27}$$

The platform captures $\frac{\epsilon}{\sigma}$ share of the startups' revenue generated through their utilization of the platform service by collecting service fees.

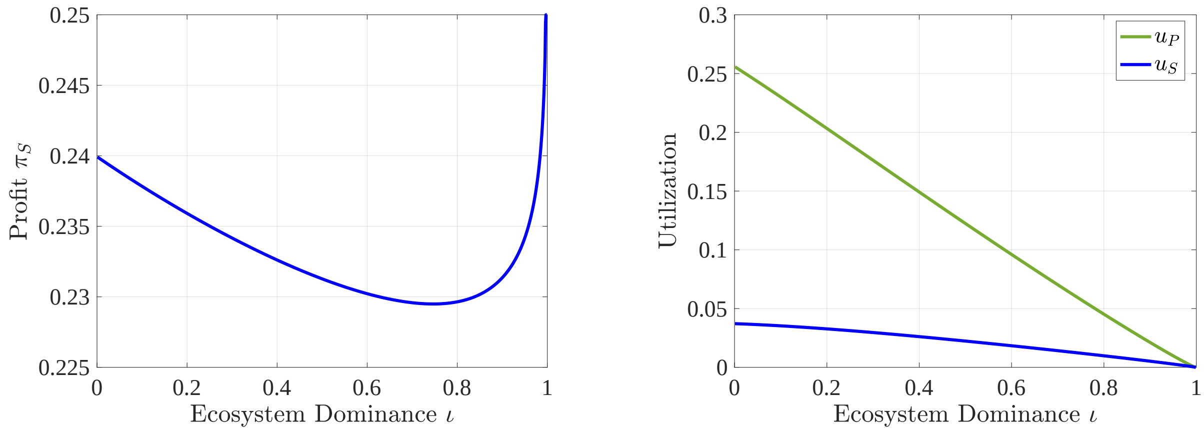
Lemma 5. *Under the platform's optimal choices for utilization:*

$$\frac{u_S}{u_P} = \left(\frac{\epsilon - \nu}{1 - \nu}\right)^{\frac{1}{1-\epsilon}} < 1,$$

where

$$\nu = \frac{\iota u_P{}^\epsilon + \epsilon(1-\iota) u_S^\epsilon}{1 + \gamma L_P \left(\iota u_P{}^\epsilon + (1-\iota) u_S^\epsilon\right)} < \epsilon.$$

[29]The utilization elasticity can be micro-founded by a model where multiple platforms offer imperfectly substitutable services and the services from different providers are aggregated via a Cobb-Douglas aggregator (see Appendix B.9 for details). In this interpretation, ϵ decreases in the number of platforms.



(a) Startup Profits

(b) Utilization of Platform Services

Figure 7: Startup Profits and Platform Utilization: Revenue Sharing Model
Note: Utilization and startup profits as a function of the platform's ecosystem dominance in the revenue sharing model. Model parameters are the same as in Table 2, plus $\epsilon = 0.1$ and $\psi = 0.05$.

The proof is in Appendix B.10. Under the optimal utilization choice, $u_S < u_P$, generating a wedge between platform and startup profits like tying does in the baseline model. There are two sources of under-utilization of the platform service by startups. First, because of its market power in the platform service market, the platform charges a markup. Second, because of the platform's dual role as a seller in the goods market, it charges an even higher markup than the standard one to increase revenue differences. To see this, note that the ratio of startup to platform utilization is less than ϵ, the under-utilization predicted by a standard monopoly model.

Endogenous Platform Time Use. What matters for the effect of acquisitions on growth is how startup profits change with the platform's ecosystem dominance. This requires numerical solution of the platform problem, where, as in the baseline model, we allow the platform to consider its effect on households' platform time use L_P when choosing utilization. Further details are in Appendix B.11.

Startup profits initially decline in ecosystem dominance so that greater ecosystem dominance discourages entry of new firms like in the baseline model (Figure 7a). However, the revenue sharing model has a second effect that as ecosystem dominance grows, the platform reduces its own per-product utilization u_P because of growing total costs (Figure 7b). Because the platform always chooses lower utilization for startups, this pushes total utilization by firms down as ecosystem dominance grows, causing households to eventually reduce their time on the platform to zero (Figure B.2a). As that happens, startup profits return to $\frac{1}{\sigma}$ as in the competitive equilibrium with no platform, hence the eventual rise in profits in Figure 7a. Because ecosystem dominance in the data should be less than the platforms' revenue share of 11%, it seems plausible that startup profits are decreasing in ι over the empirically relevant range.

7.2 Heterogeneous Firms and Exit

The final extension introduces idiosyncratic productivity dynamics at the product level to the baseline model to study exit dynamics and quality-based theories of harm for platform acquisitions: OECD (2023) suggests that a platform's ecosystem dominance may make low-quality platform products hard for entrants to displace. To formalize this intuition, we build on the theoretical framework of Luttmer (2007).

Stochastic Productivity. New entrants are born with labor productivity of 1. Productivity then fluctuates according to a geometric Brownian motion with volatility ν. We denote the log productivity of product i at time t as a_{it}. Let A_t denote the average productivity of all goods at time t.

Entry and Operating Costs. To ensure balanced growth, the entry cost $\kappa(g_t)$ now scales in $A_t N_t$. To generate exit dynamics we assume operating a product line (whether as the platform or as a startup) incurs an operating cost of $\frac{\psi}{A_t N_t}$.

Acquisitions. Search is undirected.[30] As before, meetings between startups and the platform occur at rate μ and the startups' share of the surplus is β. Acquired products follow the same productivity process as startups.

Ecosystem Dominance with Heterogeneous Firms. With heterogeneous productivity ecosystem dominance becomes

$$\iota_t = \frac{A_{Pt}}{A_t}\frac{N_{Pt}}{N_t}, \tag{28}$$

[30] In Appendix A.3 we provide evidence in favor of the assumption of random search by showing that Big Tech targets do not seem positively selected at acquisition compared to other targets in the SDC or to all other patenting firms by using patent citations as a measure of target quality.

where A_{Pt} is the average productivity of platform goods. Ecosystem dominance now comes either from supplying a large share of products as before or from having higher average productivity for a given share of products.

Pricing Equilibrium with Heterogeneous Firms. For tractability we assume constant markups so that $p_{it} = \frac{\sigma}{\sigma-1} e^{a_{it}/(1-\sigma)}$ for all goods. This yields a price index similar to equation (6). The only difference is the presence of average productivity

$$P_t = \underbrace{\frac{\sigma}{\sigma - 1}}_{\text{markup}} \times \left(\underbrace{A_t N_t}_{\text{agg. productivity}} \times \underbrace{\Big(1 + \gamma L_{P,t}(\iota_t + (1 - \iota_t)(1 - \delta_t))\Big)}_{\text{platform}} \right)^{\frac{1}{1-\sigma}}.$$

Platform Use and Tying. The solutions for platform use and tying are identical to those for the baseline model (equations (10) and (11)), substituting in the modified definition of ecosystem dominance (28).

Firm Values. Let $v_S(a)$ denote the value of a startup and $v_P(a)$ the value of a platform-owned product as functions of productivity a on a balanced growth path with growth rate g. Conditional on operating, the platform product's value evolves according to the Bellman equation

$$(\rho + g)v_P(a) = e^a \pi_P - \psi + \frac{\nu^2}{2} v_P''(a). \tag{29}$$

The flow payoff of an operating platform-owned firm is proportional to its productivity a, where the proportion is the per-unit profit π_P. The last term in (29) reflects the fact that productivity changes over time following the Brownian motion.

Similarly, a startup has the Bellman equation

$$(\rho + g)v_S(a) = e^a \pi_S - \psi + \mu\beta(v_P(a) - v_S(a)) + \frac{\nu^2}{2} v_S''(a), \tag{30}$$

where startups additionally have a flow benefit from the option value of acquisition.

Exit Dynamics. All firms have the option to exit the market. In the platform's case this means shutting down an unprofitable product line without shutting down the platform itself. The platform's exit decision is characterized by an exit threshold a_P.

The exit threshold should deliver the same value as exiting, which leads to the value-matching condition $v_P(a_P) = 0$. The exit threshold should also be optimally chosen, which leads to the smooth-pasting condition $v'_P(a_P) = 0$. Similar value matching and smooth pasting conditions for the startups deliver the startup exit threshold a_S.

Lemma 6 (Exit Threshold)**.** *On a balanced growth path, the exit thresholds are solutions to the following equations*

$$e^{a_P} = \left(1 - \frac{1}{\eta_P}\right)\frac{\psi}{\pi_P},$$

and

$$\frac{1+\eta_S}{1+\eta_P} + e^{a_P - a_S}\frac{1}{\eta_P}\left(\frac{\eta_S - \eta_P}{1+\eta_P}e^{-\eta_P(a_S - a_P)} - \eta_S\right) = \frac{\eta_P - 1}{\eta_S - 1}\left(1 - \frac{\pi_S}{\pi_P}\right),$$

where $\eta_P = \left(\frac{\rho+g}{\nu^2/2}\right)^{1/2}$ *and* $\eta_S = \left(\frac{\rho+g+\mu\beta}{\nu^2/2}\right)^{1/2}$.

Corollary 1 (Negative Selection)**.** *On a balanced growth path,* $a_S > a_P$.

Corollary 1 demonstrates the negative selection induced by ecosystem dominance: the platform will keep lower productivity product lines active compared to startups. A startup has lower profits because of tying. To justify continuing to operate, startups must have higher productivity. More startups exit the market, and, conditional on surviving, the startups tend to have a higher productivity than the platform-owned firms. Both are consistent with quality-based theories of harm suggesting ecosystem dominance and network effects allow low quality platform products to survive. Further discussion of this extension and the proof of Lemma 6 are in Appendix B.12.

8 Conclusion

Platforms intermediate a rapidly growing share of total consumption and have dual roles as intermediaries and producers. Platform-based firms have acquired startups in a wide range of industries in recent years, often as a way to expand their product offerings and "digital ecosystems." Regulators show a keen interest in understanding the effects of platform-based firms' acquisitions on growth, but economic theory and evidence have lagged behind.

This paper aims to fill that gap. First, contrary to popular belief, a large share of platform acquisitions are cross-industry, motivating us to move beyond "killer acquisitions." Cross-industry acquisitions by platforms have competing effects on new entrants' incentives. As commonly noted in Silicon Valley, the chance of being acquired is itself a strong motive for entry. At the same time, acquisitions expand a platform's presence into new markets and make it less costly for the platform to reduce demand for third party sellers' products in favor of its own. Regulations targeted at these other activities likely matter much more for welfare than stricter acquisition policy. One interesting direction for future research is to consider how competition policy affects the incentives of platform firms to improve their platform technologies themselves, since digital platforms require significant investment to develop.

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A Data Appendix

A.1 Data Sources

The SDC Platinum data is described in the main text. The sources for other data series mentioned in the text are:

1. **Industry specific GDP** Bureau of Economic Analysis, Annual Value added by Industry as a Percentage of Gross Domestic Product, Tables TVA110-A for the years 2017 onwards and TVA106-A for the preceding years.

2. **Retail Sales** U.S. Census Bureau, Retail Sales: Retail Trade [MRTSSM44000USS] retrieved from FRED, Federal Reserve Bank of St. Louis.

3. **Final Consumption Expenditure** Organization for Economic Co-operation and Development, Private Final Consumption Expenditure in United States [USAPFCEQDSNAQ], retrieved from FRED.

4. **E-commerce Retail Sales** U.S. Census Bureau, E-Commerce Retail Sales as a Percent of Total Sales [ECOMPCTSA] retrieved from FRED.

5. **GAFAM revenue** Total Revenues (Compustat code: revt) as reported in the companies' annual income statement of 2021.

6. **Total U.S. non-farm, non-financial revenue** Annual flow of funds tables on FRED St. Louis (code: BOGZ1FA106030005A. Definition: Nonfinancial Corporate Business; Revenue from Sales of Goods and Services, Excluding Indirect Sales Taxes (FSIs), Transactions).

A.2 Summary Statistics for Acquisitions

Summary statistics for platform acquisitions are in Table A.1. The GAFAM group did 133 acquisitions per firm from 2010-2020, more than the other three groups of large acquirers, giving us 665 total deals for this group.[31] In terms of cross-industry acquisitions, they were *more* likely to acquire firms in other industries (the granularity of the industry classifications in the SDC are roughly equivalent to NAICS3 categories). They also paid a significantly higher acquisition premium, defined as $\left(\frac{\text{deal price}}{\text{pre-acq. price}} - 1\right) \times 100$, though coverage of this variable is only available for six publicly listed targets. GAFAM firms were more likely to acquire young firms, even

[31] Only 467 of these have non-missing entries for all three industry codes for the targets.

	GAFAM	Top 25 HT	Top 25 PE	Top 25 S&P
	Deal Characteristics			
Deals per firm	133.5	82.1	115.9	84.0
Cross-industry Share, SDC def. %	68.7	59.4	48.9	49.4
M&A Premium, %	83.1	45.1	45.7	47.4
	Target Characteristics			
Age	7.9	13.3	17.6	13.8
Age - Ind Avg. Age	-4.6	0.0	6.5	3.1
Employees	4582	9020	1978	376
Emp.-Ind Avg. Emp.	879.7	1380.9	1928.4	305.3
Emp./Total Ind. Emp	2.1	1.0	0.2	0.2
Patents	20.6	18.0	5.2	4.8
Patents/Ind. Avg. Avg. Patents	25.3	16.0	2.8	0.9
Share No Patents	61.6	69.6	83.2	82.7
EBITDA <0 LTM, %	38.2	22.1	19.6	22.1
Pre-Tax Inc. <0 LTM, %	50.0	41.5	28.0	30.1

Table A.1: Source: SDC Platinum, 2010-2020, restricting attention to SDC-classified high tech targets. “GAFAM” is Google, Apple, Facebook, Amazon, and Microsoft. The three other groups are constructed following Jin, Leccese, and Wagman (2023a): the largest non-GAFAM acquirers labelled as high-tech by Forbes’ ranking of Top 100 Digital Companies (“Top 25 Hi-Tech”), the largest private equity firms by Private Equity International (“Top 25 PE”) and the other largest 25 firms by number of acquisitions in the S&P database (“Top 25 S&P”). “LTM” = last twelve months.

controlling for average firm age in the same industry. Targets of GAFAM had more patents relative to targets of other acquirers as well as relative to other firms in their industry. On the other hand they were less likely to have positive earnings before interest, taxes, depreciation, and amortization (EBITDA) or pre-tax income in the 12 months prior to acquisition than targets of other firms, and, as we show in Section A.3, these patents did not receive more citations than comparable patenting firms or non-GAFAM targets.

A.3 Evidence for Random Search in Heterogeneous Firms Model

One concern is that acquirers, particularly platforms where startups already sell their products, may not meet startups at random for an acquisition. If platforms tend to acquire only high quality startups it could change the predictions of the model. To investigate this in the data, we focus on the GAFAM targets with at least one patent prior to acquisition and use patent citations to measure a target firm's quality relative to otherwise similar firms to check for selection on quality at acquisition.[32] This gives us 119 platform targets. For each of these firms we build two control groups:

1. Other targets in the SDC Platinum database (yields 204 control firms on average) with the same:
   - NAICS6 industry code
   - Year of first patent (± 5 years).
   - Year of acquisition or later.
2. Other patenting firms in the USPTO PatentsView data (yields 909 control firms on average) with:
   - Cosine similarity $\theta_{ij} > 0.9$ of CPC codes, computed as

     $$\theta_{ij} = \frac{F_i F_j'}{(F_i F_i')^{\frac{1}{2}} (F_j F_j')^{\frac{1}{2}}},$$

     where $F_i = \{F_{i,CPC_1}, \ldots, F_{i,CPC_{132}}\}$ is a vector capturing the distribution of i's patents across 132 CPC codes following Bloom, Schankerman, and Van Reenen (2013). Each element $F_{i,CPC_k} = \frac{n_{i,CPC_k}}{n_i}$ is the share of firm i's patents in CPC code k in the total number of CPC codes of firm i's patents, with $n_i = \sum_{k=1}^{132} n_{i,CPC_k}$.
   - Same year of first patent (± 1 years)

We then compute, for each target firm i:

$$\xi_i \equiv \left\{ \frac{\text{5 year forward citations of GAFAM target } i}{\text{avg. 5 year forward citations of control firms' patents}} \right\},$$

including all patents granted to firm i and firm i's control group prior to firm i's acquisition date.

[32] It is difficult to measure startup quality for startups without patents. Table A.1 shows that for possible measures including EBITDA and net income, GAFAM targets are more likely than other targets to have negative profits prior to acquisition, pointing to possible *negative* selection.

If $\xi_i > 1$, this suggests firm i was higher quality than its control group in terms of citations received to its patents at the time of acquisition. Using Control Group 1, only 36% of GAFAM targets have more citations than the average control firm (that is, $\xi_i > 1$). For Control Group 2 the share is 44%. The median ξ_i across all GAFAM targets is 0.49 using Control Group 1 and 0.78 using Control Group 2 meaning GAFAM targets tend to receive *fewer* citations than comparable firms. However the means are 3.04 and 2.91, respectively, suggesting that there are a few very high quality targets in the GAFAM group. Still we take this overall as evidence in favor of random search by GAFAM in the M&A market and are reassured by the similarities of the findings regardless of the control group (other patenting targets or all patenting firms).

B Model Appendix

B.1 Derivation of Household's Problem

We start with the expenditure minimization problem:

$$\min \int_0^{N_t} p_{i,t} c_{i,t} di,$$

s.t.

$$C_t = \left[\int_0^{N_t} \alpha_{it}^{\frac{1}{\sigma}} c_{it}^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}}.$$

The solution to this problem gives the standard CES demand curve

$$c_{it} = \frac{\alpha_{it} p_{it}^{-\sigma}}{P_t^{-\sigma}} C_t,$$

where

$$P_t = \left(\int_0^{N_t} \alpha_{it} p_{i,t}^{1-\sigma} di \right)^{\frac{1}{1-\sigma}}.$$

The following Bellman equation characterizes the household's optimization problem:

$$\rho W_t(a) = \max_{C_t, L_t} \log C_t - L_t + \dot{a} W_t'(a) + \dot{W}_t(a),$$

where

$$\dot{a} = r_t a + \Pi_t + L_t - P_t C_t.$$

The first-order conditions for labor and consumption are:

$$\frac{1}{C_t} = P_t W_t'(a)$$

$$1 = W_t'(a)$$

For both conditions to hold, it must be that $P_t C_t = 1$ for any t. These two conditions also imply that $W_t'(a) = 1$ for any t and any a. Using this result, we can re-write the Bellman equation as:

$$\rho W_t(a) = \log C_t(a) - L_t(a) + r_t a + \Pi_t + L_t(a) - P_t C_t(a).$$

Differentiating both sides of the equation with respect to a, we have

$$\rho = r_t.$$

B.2 Derivation of Firm Values

We derive the detrended firm values in this section. To start, we denote the value of platform firms as V_{Pt} and the value of standalone firms (startups) as V_{St}. From the definition of the detrended values, $V_{Pt}N_t = v_{Pt}$ and $V_{St}N_t = v_{St}$.

The equations that determine the firm values are:

$$r_t V_{Pt} = \pi_{Pt}\frac{1}{N_t} + \dot{V}_{Pt}$$

and

$$r_t V_{St} = \pi_{St}\frac{1}{N_t} + \mu\beta\left(V_{Pt} - V_{St}\right) + \dot{V}_{St}.$$

With the chain rule, we can write

$$\dot{V}_{Pt}N_t + V_{Pt}\dot{N}_t = \dot{v}_{Pt}$$

and

$$\dot{V}_{St}N_t + V_{St}\dot{N}_t = \dot{v}_{St}.$$

Substituting the time derivatives, we have

$$r_t V_{Pt} = \pi_{Pt}\frac{1}{N_t} + \frac{\dot{v}_{Pt} - V_{Pt}\dot{N}_t}{N_t}$$

and

$$r_t V_{St} = \pi_{St}\frac{1}{N_t} + \beta\mu\left(V_{Pt} - V_{St}\right) + \frac{\dot{v}_{St} - V_{St}\dot{N}_t}{N_t}.$$

Multiplying both sides by N_t and using the definition for the detrended values, we have

$$(r_t + g_t)V_{Pt} = \pi_{Pt} + \dot{v}_{Pt}$$

and

$$(r_t + g_t)V_{St} = \pi_{St} + \beta\mu\left(v_{Pt} - v_{St}\right) + \dot{v}_{St}.$$

B.3 Proof of Lemma 2

Proof. Taking equation (18), we first want to prove that $\frac{dg_t}{dt} > 0$. To do so, totally differentiate both sides of the equation with respect to t:

$$\frac{dg_t}{dt}\kappa = -\frac{d\pi_s}{d\iota}\iota_o^* \exp\left(-\int_0^t g_\tau d\tau\right) g_t > 0,$$

where we used the result $\frac{d\pi_s}{d\iota} < 0$. To prove the statement regarding g_0, we note that when $t = 0$, the free entry condition becomes:

$$(\rho + g_0)\kappa = \pi_s(\iota_o^*) < \pi_s(\iota_o^*) + \mu\beta(v_{p,o}^* - \kappa),$$

where the inequality uses the fact that in the old BGP, $\mu\beta(v_{p,o}^* - \kappa) > 0$. □

B.4 Proof of Lemma 3

Proof. To show the statement regarding g_n^* and g_o^*, we note that in the new BGP, $\iota_n^* = 0$. Thus $\pi_{s,n}^* \equiv \pi_s(\iota_n^*) = \frac{1}{\sigma}$. Suppose the condition in the lemma is true; we want to prove that $g_n^* > g_o^*$ by contradiction. Contrary to the statement, suppose $g_n^* \leq g_o^*$. From the free-entry condition in the old BGP:

$$(\rho + g_n^*)\kappa \leq (\rho + g_o^*)\kappa = \pi_{s,o}^* + \beta\mu\left(\frac{\pi_{p,o}^*}{\rho + g_o^*} - \kappa\right) < \frac{1}{\sigma},$$

where in the first inequality, we used the assumption $g_n^* \leq g_o^*$, and in the last inequality, we used the condition in the lemma. This is a contradiction. This proves that under the condition of the lemma, $g_n^* > g_o^*$. The same logic can prove the opposite direction. □

B.5 Effect of Local Changes in Acquisition Rate

Section 4 considered a complete ban on acquisitions. Here we derive the analog to Lemma 3 for local changes in the acquisition rate around the original steady state, i.e., blocking a marginally higher fraction of deals. There are two countervailing effects. Given a fixed growth rate, a lower acquisition rate decreases the BGP ecosystem dominance (equation (16)). Lower ecosystem dominance reduces tying, which increases π_S and encourages entry. We refer to this as the *discouragement effect* of ecosystem dominance; on the other hand, a slower pace of acquisitions discourages entry by lowering the option value of acquisition. We refer to this as the *rent-sharing effect*.

Lemma 7. *A small decrease in μ (stricter acquisition policy) leads to a higher BGP growth rate if*

$$\underbrace{\beta\left(\frac{\pi_P}{\kappa(g^*)(\rho+g)} - 1\right)}_{\textit{M\&A Premium}} < \underbrace{\frac{\pi_S}{\kappa(g^*)}}_{\textit{ROE of Target Firm}} \times \underbrace{\frac{d\log \pi_s}{d\iota}}_{\textit{Profit - Dominance Elasticity}} \times \underbrace{\frac{d\iota}{d\mu}}_{\textit{Impact on Dominance}}$$

The impact of the rent-sharing effect is summarized by the share of value accrued to the standalone firms as a fraction of their standalone value when they are acquired, which is the measure of the acquisition premium from our model. The direct effect is measured by the elasticity of tying with respect to ecosystem dominance.

We further break down the discouragement effect into three parts. First, the direct impact of a decrease in the acquisition rate reduces ecosystem dominance. This is measured by

$$\frac{d\iota}{d\mu} = \frac{g}{(g+\mu)^2}.$$

Secondly, the reduction in the ecosystem dominance increases the profits of the startups because the platform reduces tying, measured by

$$\frac{d \log \pi_s}{d\iota} = \frac{\gamma L_P(1-\delta)}{1+\gamma L_P(\iota + (1-\delta)(1-\iota))}.$$

Lastly, this increase in the profits encourages more entry and more growth if the standalone firms are valued mostly due to their profits, measured by the profits as a fraction of firm value, the return-to-equity (ROE) of targets in the data.

Proof. To derive the impact of a change in acquisition rate on the long-run growth, we utilize the implicit function theorem. More precisely, we define a function

$$T(g,\mu) \equiv (\rho+g)\kappa(g) - \pi_s\left(\frac{\mu}{\mu+g}\right) - \beta\mu\left(\frac{\pi_P}{g+\rho} - \kappa(g)\right).$$

The balanced-growth values are such that $T(g^*,\mu^*) = 0$. The first-order impact of a small increase in μ on g can be written as:

$$\frac{dg^*}{d\mu^*} = -\frac{\partial_\mu T(g^*,\mu^*)}{\partial_g T(g^*,\mu^*)}.$$

We now calculate the terms separately. In the first step, we want to show that $\partial_g T(g^*,\mu^*) > 0$:

$$\partial_g T(g^*,\mu^*) = \kappa(g^*) + (\rho+g^*)\kappa'(g^*) + \pi'_S\left(\frac{\mu}{g+\mu}\right)\frac{\mu}{(g+\mu)^2} + \beta\mu(\frac{\pi_P}{(g+\mu)^2} + \kappa'(g)).$$

Since every term on the RHS is positive, we conclude that $\partial_g T(g^*,\mu^*) > 0$. Thus, $\frac{dg^*}{d\mu^*} > 0$ if and only if $\partial_\mu T(g^*,\mu^*) < 0$:

$$\partial_\mu T(g^*,\mu^*) = -\left(\pi'_S\left(\frac{\mu}{\mu+g}\right)\frac{g}{(g+\mu)^2} + \beta\left(\frac{\pi_P}{g+\rho} - \kappa(g)\right)\right).$$

Thus $\frac{dg^*}{d\mu^*} > 0$ if and only if

$$\beta\left(\frac{\pi_P}{g+\rho} - \kappa(g)\right) > -\pi'_S\left(\frac{\mu}{\mu+g}\right)\frac{g}{(g+\mu)^2}.$$

To convert the equation into the form in the lemma, we expand the derivatives and divide both sides of the inequality by $\kappa(g)$. $\square$

B.6 Planner's Solution

We characterize the solution to

$$\rho W^{SP}(N) = \max_{L_P, L_Y, \dot{N}} \log\left((1+\gamma L_P)N\right)^{\frac{1}{\sigma-1}} L_Y - \left(L_P + L_Y + \kappa\left(\frac{\dot{N}}{N}\right)\frac{\dot{N}}{N}\right) + \dot{N} W^{SP\prime}(N).$$

Optimal entry of the planner equates the social value of a new firm to the static entry costs:

$$W^{SP\prime}(N)N = \kappa'\left(\frac{\dot{N}}{N}\right)\frac{\dot{N}}{N} + \kappa\left(\frac{\dot{N}}{N}\right).$$

Using the definition $g = \frac{\dot{N}}{N}$

$$W^{SP\prime}(N)N = \kappa'(g)\,g + \kappa(g).$$

Differentiating both sides with respect to time:

$$W^{SP\prime}(N)\dot{N} + W^{SP\prime\prime}(N)N\dot{N} = \kappa''(g)\,g\dot{g} + \kappa'(g)\,\dot{g}.$$

Differentiating the Bellman equation, we have

$$\rho W^{SP\prime}(N) = \frac{1}{\sigma-1}\frac{1}{N} + \kappa'\left(\frac{\dot{N}}{N}\right)\frac{\dot{N}}{N}\frac{\dot{N}}{N^2} + \kappa\left(\frac{\dot{N}}{N}\right)\frac{\dot{N}}{N^2} + \dot{N}W^{SP\prime\prime}(N).$$

From the first order condition:

$$\rho W^{SP\prime}(N) = \frac{1}{\sigma-1}\frac{1}{N} + W^{SP\prime}(N)\frac{\dot{N}}{N} + \dot{N}W^{SP\prime\prime}(N)$$

From the differentiated first-order condition:

$$\rho W^{SP\prime}(N) = \frac{1}{\sigma-1}\frac{1}{N} + \frac{1}{N}\left(\kappa''(g)\,g\dot{g} + \kappa'(g)\,\dot{g}\right)$$

Multiplying both sides by N and use the first-order condition again

$$\rho\left(\kappa'(g)\,g + \kappa(g)\right) = \frac{1}{\sigma-1} + \left(\kappa''(g)\,g + \kappa'(g)\right)\dot{g}.$$

B.7 Proof of Lemma 4

Proof. Under constant markups, the markup component of the equilibrium with or without acquisitions stays the same, and thus the markup component is irrelevant to the welfare impact. In addition, we argued that the utilization component also stays constant for interior tying. Thus we can write the change in welfare as

$$\Delta W = \int_0^\infty e^{-\rho t}\left(\frac{1}{\sigma-1}\int_0^t (g_\tau - g_o^*)d\tau - \kappa(g_t - g_o^*)\right)dt.$$

We isolate the first component and simplify it:

$$\frac{1}{\sigma-1}\int_0^\infty\int_0^t (g_\tau - g_o^*)d\tau dt = \frac{1}{\sigma-1}\int_0^\infty\int_\tau^\infty e^{-\rho t}(g_\tau - g_o^*)dtd\tau$$
$$= \frac{1}{\rho(\sigma-1)}\int_0^\infty (g_\tau - g_o^*)dtd\tau,$$

where the first equality changes the order of integration, and the second equality evaluates the inner integral. Plugging this back into the welfare formula, we reach the result in the lemma. □

B.8 Variable Markup Solution

Let the platform's quality $\alpha_P = (1+L_P\gamma)$ and startups' quality $\alpha_S = (1+L_P\gamma(1-\delta))$. The first order conditions to the platform's problem (25) of choosing tying and prices are

$$FOC_{p_P} \quad \frac{1}{p_P}\frac{\sigma-(\sigma-1)s_P}{(\sigma-1)(1-s_P)} + \frac{(p_P-1)}{(\sigma-1)}\left[\left(\frac{\frac{\partial\alpha_P}{\partial p_P}}{\alpha_P} - \frac{\frac{\partial\alpha_S}{\partial p_S}}{\alpha_S}\right)\right] = 0 \tag{31}$$

$$FOC_\delta \quad \left[\frac{\frac{\partial\alpha_P}{\partial\delta}}{\alpha_P} - \frac{\frac{\partial\alpha_S}{\partial\delta}}{\alpha_S}\right] + \left[\frac{(\sigma-1)}{p_P}\frac{s_P}{1-s_P}\right] = 0 \tag{32}$$

$$\text{where} \quad s_P \equiv \frac{\iota\alpha_P p_P^{1-\sigma}}{\left(\iota\alpha_P p_P^{1-\sigma} + (1-\iota)\alpha_S p_S^{1-\sigma}\right)} \text{ is the platform's market share.} \tag{33}$$

The first term in (31) is the one that appears in the standard variable markup case where α_P and α_S are different but constant and a firm with a non-zero mass of varieties imperfectly competes with a competitive fringe of standalone firms. As in the standard problem this term captures the platform's trade-off between its extensive and intensive profit margin when raising the price. The second term captures the marginal effect on the quality spread between the platform and the startups induced by changing time use through prices.

B.9 Micro-Foundation for the Platform Utilization Elasticity

This section provides a micro-foundation for the platform utilization elasticity and links it explicitly to competition between different platforms in the platform services market. Suppose there are J different platforms providing services in the economy.

The final quality of an individual product is determined by a Cobb-Douglas aggregator across the utilization of these platforms. More specifically,

$$U = \Pi_{j=1}^{J} u_j^{\frac{1}{J}}.$$

The standalone firms take as given the prices set by platforms, $\{q_j\}_{j=1}^{J}$. Given these prices, the profit maximization problem of an individual firm for the service from platform j is

$$\max_{u_j} \frac{1}{\sigma} \frac{1 + \gamma L_P U}{1 + \gamma L_P(\iota U_P + (1-\iota)U_S)} - \sum_{j=1}^{J} q_j u_j.$$

Taking the first-order condition, we have the optimal utilization of each individual platform

$$q_j = \frac{1}{\sigma} \frac{\frac{1}{J}\gamma L_P u_j^{1/J-1} \Pi_{k\neq j} u_k^{1/J}}{1 + \gamma L_P(\iota U_P + (1-\iota)U_S)}$$

Although fully characterizing the equilibrium outcome with multiple strategic platforms requires us to impose additional structures on the equilibrium, which is outside of the scope of this paper, we note that if we relabel $\epsilon = \frac{1}{J}$, the demand curve from the standalone firms resembles the one considered in the main text:

$$q_j = \frac{1}{\sigma} \frac{\epsilon \gamma \tilde{L}_j u_j^{\epsilon-1}}{1 + \gamma L_P(\iota U_P + (1-\iota)U_S)},$$

with $\tilde{L}_j = L_P \Pi_{k\neq j} u_k^{1/J}$. In this micro-founded model, ϵ is related to the competition in the market for platform services. More precisely, ϵ decreases in the number of platforms in the economy, and vice versa.

B.10 Proof of Lemma 5

Proof. Writing out the first-order conditions for u_p and u_s:

$$\frac{\gamma L_P}{\sigma} \frac{\epsilon\gamma u^{\epsilon-1}\left(1 + \gamma L_P\left(\iota(u^*)^\epsilon + (1-\iota)U^\epsilon\right)\right) - \epsilon\gamma u^{\epsilon-1}\left(\iota(u^*)^\epsilon + \epsilon(1-\iota)U^\epsilon\right)}{\left(1 + \gamma L_P\left(\iota(u^*)^\epsilon + (1-\iota)U^\epsilon\right)\right)^2} = \psi$$

and

$$\frac{\gamma L_P}{\sigma} \frac{\epsilon^2\gamma U^{\epsilon-1}\left(1 + \gamma L_P\left(\iota(u^*)^\epsilon + (1-\iota)U^\epsilon\right)\right) - \epsilon\gamma U^{\epsilon-1}\left(\iota(u^*)^\epsilon + \epsilon(1-\iota)U^\epsilon\right)}{\left(1 + \gamma L_P\left(\iota(u^*)^\epsilon + (1-\iota)U^\epsilon\right)\right)^2} = \psi.$$

Taking the ratio and canceling redundant terms:

$$\frac{\epsilon - \nu}{1 - \nu} \left(\frac{u_s}{u_p}\right)^{\epsilon-1} = 1$$

where $\nu = \frac{\iota u_P{}^\epsilon + \epsilon(1-\iota)u_S^\epsilon}{1+\gamma L_P\left(\iota u_P{}^\epsilon + (1-\iota)u_S^\epsilon\right)}$. For $u_S > 0$, $\nu < \epsilon$. Inverting this equation, we have the result as in the lemma.

B.11 Revenue Sharing With Endogenous Time Use

We prove that platform utilization is always higher than startup utilization when platform time use is endogenous. With endogenous time use L_P, the platform's profit maximization problem becomes

$$\max_{u_S,u_P} \iota\pi_P + (1-\iota)\frac{\epsilon}{\sigma}\frac{\gamma L_P u_S^\epsilon}{1+\gamma L_P\left(\iota u_P^\epsilon + (1-\iota)u_S^\epsilon\right)} - (\iota u_P + (1-\iota)u_S)\psi. \qquad (34)$$

subject to:

$$L_P = \frac{1}{\sigma-1} - \frac{1}{\gamma(\iota u_P^\epsilon + (1-\iota)u_S^\epsilon)}.$$

Define $P \equiv (\iota u_P^\epsilon + (1-\iota)u_S^\epsilon)$, $P_e \equiv (\iota u_P^\epsilon + \epsilon(1-\iota)u_S^\epsilon)$, and $D \equiv (1+\gamma L_P\left(\iota u_P^\epsilon + (1-\iota)u_S^\epsilon\right))^2$. The first order conditions are

$$[u_P]: \frac{\epsilon}{\sigma}\iota u_P^{\epsilon-1}\left(\frac{(1+\gamma L_P P)(\frac{P_e}{P^2}+\gamma L_P) - (\iota + \gamma L_P P_e)(\frac{P}{P^2}+\gamma L_P)}{D}\right) = \iota\psi,$$

$$[u_S]: \frac{\epsilon}{\sigma}(1-\iota)u_S^{\epsilon-1}\left(\frac{(1+\gamma L_P P)(\frac{P_e}{P^2}+\epsilon\gamma L_P) - (\iota + \gamma L_P P_e)(\frac{P}{P^2}+\epsilon\gamma L_P)}{D}\right) = (1-\iota)\psi.$$

To show that $u_P > u_S$, divide the first order conditions:

$$\frac{u_S}{u_P} = \left(\frac{\frac{P_e}{P^2} - \iota\frac{P}{P^2} + \epsilon\gamma L_P(1-\iota) + \epsilon(\gamma L_P)^2(P-P_e)}{\frac{P_e}{P^2} - \iota\frac{P}{P^2} + \gamma L_P(1-\iota) + (\gamma L_P)^2(P-P_e)}\right)^{\frac{1}{1-\epsilon}}.$$

For $u_P > u_S$, it must be that

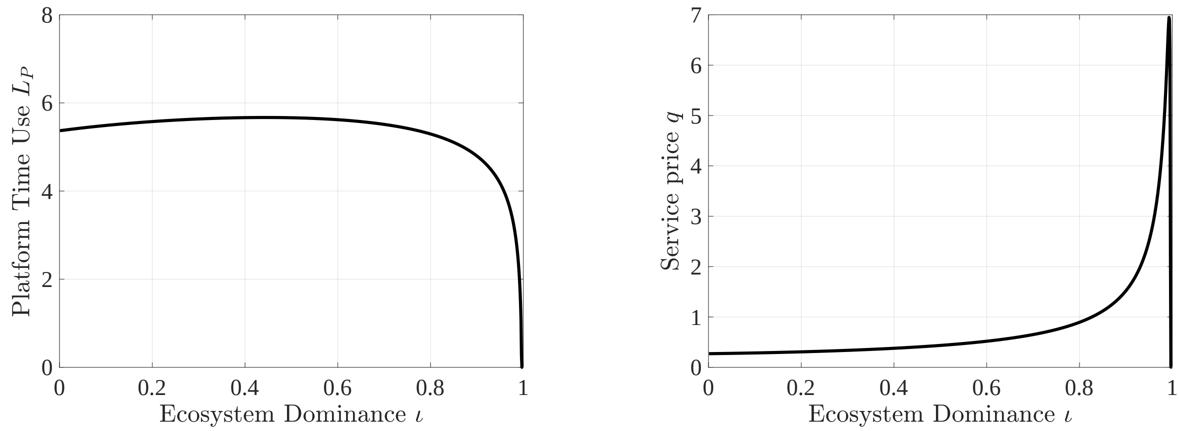
$$\frac{P_e}{P^2} - \iota\frac{P}{P^2} + \gamma L_P(1-\iota) + (\gamma L_P)^2(P-P_e) > \frac{P_e}{P^2} - \iota\frac{P}{P^2} + \epsilon\gamma L_P(1-\iota) + \epsilon(\gamma L_P)^2(P-P_e)$$

$$(1-\epsilon)\gamma L_P(1-\iota) + (1-\epsilon)(\gamma L_P)^2(P-P_e) > 0.$$

All terms on the left hand side are positive (note $P - P_e = (1-\epsilon)(1-\iota)u_S^\epsilon$), so the proof is complete.

B.12 Heterogeneous Firms Extension

In discussion of the dynamic equilibrium, we focus on a balanced growth path where aggregate productivity $A_t N_t$ grows at a constant rate. Growth in a balanced growth path for this economy comes from creating new products net of exit. To characterize the entry-exit decisions of firms on a balanced growth path with a growth rate of g,



(a) Platform Time Use

(b) Platform Service Price q

Figure B.2: Platform Time Use and Platform Service Price, Revenue Sharing Model

Note: Service price and platform time use as functions of ecosystem dominance in the revenue sharing model. Model parameters are the same as in Table 2, plus $\epsilon = 0.1$ and $\psi = 0.05$.

we characterize the value of product lines, depending on whether they are owned by a startup or by the platform.

Both the value functions of the platform-owned goods and the standalone firms can be solved in closed-form, given a growth rate such that $\rho + g > \frac{\nu^2}{2}$. These closed-form solutions are convenient for computation of the model but offer similar economic insights as in equation (29) and (30).

Lemma 8 (Value Function). *On a balanced growth path, the equilibrium value of firms are given by the following equations:*

$$v_P\left(a\right) = \frac{1}{\rho + g - \frac{\nu^2}{2}} \pi_P e^a + \frac{\psi}{\rho + g} \left(\frac{1}{1 + \eta_P} e^{-\eta_P (a - a_P)} - 1 \right),$$

and

$$v_S\left(a\right) = v_P(a) - \frac{\pi_P - \pi_S}{g + \rho + \mu\beta - \frac{\nu^2}{2}} e^a - e^{-\eta_S (a - a_S)} \left(v_P(a_S) - \frac{\pi_P - \pi_S}{g + \rho + \mu\beta - \frac{\nu^2}{2}} e^{a_S} \right).$$

C Quantitative Appendix

Figure C.3 plots the merger premium in each steady state for different values of the platform technology γ. As the platform technology grows, the merger premium increases because the difference in the value of a product in the hands of the platform versus the startup grows as the technology grows.

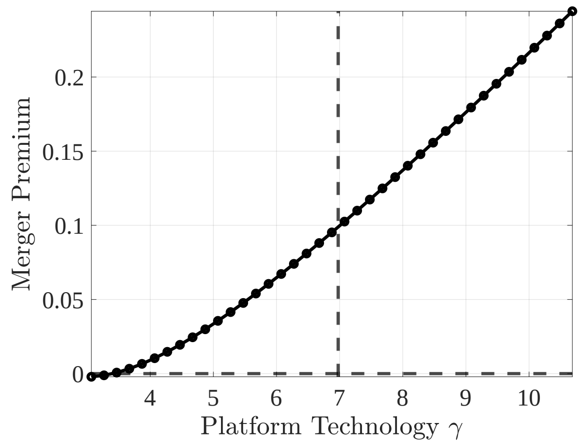


Figure C.3: Merger Premium Increases in Platform Technology

Note: Merger premium as a function of γ. See section 6.4 for details on the exercise. Parameter values in Table 2.