Merger Policy for Platforms: A Growth Theory Perspective*

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Abstract

Should Big Tech firms be barred from acquiring other firms? We examine this question using a growth model with platform-based consumption. The platform supplies some products, while startups supply the rest, with the platform intermediating digital-sector consumption. Acquisitions expand the platform's product set and have competing effects on startup entry. Theoretically, banning acquisitions lowers growth in the short run but may raise it in the long run. However, when calibrated to U.S. household time-use data on digital platforms, the model predicts slower growth in both the short and long run, generating a small overall welfare loss from an acquisition ban.

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1 Introduction

Policymakers are increasingly focused on competition and growth in digital markets, where platform-based firms sell wide-ranging "digital ecosystems" of products, intermediate third party sales, and frequently acquire other firms. Legislators in the United States, United Kingdom, and European Union have proposed banning the "GAFAM" (Google, Amazon, Facebook, Apple, and Microsoft) firms from acquiring other firms because of their role as ''gatekeepers" or ''covered platforms." Much of the concern is about the effect of these acquisitions on economic growth, in contrast to the longstanding approach of competition authorities to evaluate static tradeoffs between market power and 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 that gap. 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).

Our main contribution is to develop a novel growth model with platform-based consumption where acquisitions have both positive and negative effects on growth to capture the *dynamic* tradeoffs regulators face. The negative effects of platform acquisitions are due to cross-industry spillovers to non-acquired firms, suggesting that a model where the platform's ecosystem affects many different industries is needed to understand these forces. Our theory allows us to (i) derive a condition under which an acquisition ban increases the economy's steady state growth rate, (ii) analytically characterize the path of the growth rate after an acquisition ban,

yielding the novel insight that the growth rate initially falls after a ban even if it increases in the long run, and (iii) show that alternative competition policies can more directly address the harms of so-called "ecosystem dominance."[1] The final contribution of the theoretical framework is that it is simple enough to accommodate many relevant extensions. We illustrate three of these, including competition between platforms, in the final section of the paper.

We then bring the model to the data to quantitatively evaluate merger policy. The positive entry-for-buyout effect of platform acquisitions is slightly stronger than the negative ecosystem dominance effect. An acquisition ban therefore reduces welfare by approximately 0.21% in consumption-equivalent terms. The small, negative effect of a ban is fairly robust to alternative calibrations of the model. The alternative competition policies indicated by the theory improve welfare 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 that platforms can engage in to tilt demand 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).[2] These practices are relevant in merger decisions: the European Commission rejected Amazon's $1.4 billion dollar bid for iRobot because the "dual role of Amazon as platform operator and market participant" could enable Amazon to degrade third-party sellers' access to its platform and might have negative effects on innovation and product quality (European Commission 2024).

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

[1]The FTC Merger Guidelines issued December 2023 embraced an ecosystem dominance theory of harm for the first time (Federal Trade Commission and U.S. Department of Justice 2023).

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

number and quality of products available on the platform and choose how much to use the platform each period. The platform faces a tradeoff when it decides how much to engage in 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, acquisitions generate a surplus. From a consumer perspective, acquisitions increase the quality of the target firm's product; the target's sales increase post-acquisition. If this were the only effect of acquisitions, they would be unambiguously good for consumers. But acquisitions also 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.

Platform acquisitions have ambiguous effects on growth and welfare in the long run. An acquisition ban increases growth when the option value of acquisition is low compared to the responsiveness of startup profits to ecosystem dominance. Even if an acquisition ban increases growth in the long run, it necessarily involves sacrificing growth in the short run because entry-for-buyout incentives change immediately while the costs of tying diminish slowly as the platform's ecosystem dominance erodes through the entry of new startups.

The model features one novel parameter, the platform's appeal technology, that we calibrate using the model-implied mapping from this parameter to the observed time households spend on the platform. In the calibrated model, an acquisition ban reduces steady-state consumption-equivalent welfare by 0.15% by lowering the steady-state entry rate. Since the entry rate declines even more sharply in the short run, the transition path features a larger welfare loss: discounted consumption-equivalent welfare falls by 0.21%. A ban on tying increases welfare, primarily by correcting households' platform under-utilization due to tying, but also by increasing the entry rate.

We consider three extensions to the theory. First, competition between plat-

forms dampens the welfare effects of an acquisition ban because tying is lower. A second extension where the platform sells its technology to startups for a fee (instead of directly tying) provides 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. The final extension allows for idiosyncratic productivity shocks and exit to address quality-based theories of harm for platform mergers (OECD 2023). Tying raises the platform's profits on low-productivity goods and makes them less likely to exit, whereas startups exit too quickly from a planner's perspective, consistent with the idea that ecosystem dominance makes it hard to displace low-quality incumbents. Our framework is also well-suited to study how platforms' incentives to improve their own technology or introduce new products interact with competition policy. We leave these issues to future work and focus here on the entry effects of an acquisition ban.

Finally, we document new stylized facts about platform firms and their acquisitions. The cross-industry acquisitions we study constitute about 70% of all platform acquisitions. These span a large set of industries: industries with at least one platform acquisition between 2010-2022 account for 55% of GDP. 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 contributes to two strands of literature in macroeconomics. The first studies the market for firms and its effects on firm dynamics, growth, and welfare (David 2020; Cavenaile, Celik, and Tian 2021).[3] We follow this literature in focusing on the macroeconomic consequences for allocative efficiency instead of solely on consumer welfare. 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

[3]See also Atalay, Hortaçsu, and Syverson (2014), Bhandari and McGrattan (2020), Weiss (2023), Celik, Tian, and Wang (2022), Chatterjee and Eyigungor (2023), Liu (2023), Berger et al. (2025), Bhandari, McGrattan, and Martellini (2025). Relatedly Akcigit, Celik, and Greenwood (2016) study the market for patents and Pearce and Wu (2023) study the market for trademarks.

but may "kill" competing products in the same industry.[4] Ederer, Seibel, and Simcoe (2025) find that most acquisitions by large tech firms result in an increase in citations to target patents rather than a decrease, an indication that killer acquisitions by platforms are rare. Our contribution is to instead introduce a new mechanism about *cross-industry* acquisitions given their importance in the data. In our model, the platform is special because it provides a service that is complementary to other goods in the digital sector.[5] Acquisitions enhance the quality of the acquired firm and are bilaterally efficient, but have negative spillovers to non-acquired firms. We view our work on cross-industry acquisitions as complementary to the literature on killer acquisitions.

The second literature studies the emergence and welfare effects of platforms[6] and of digital technologies more broadly.[7] 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 and Kirpalani and Philippon (2020) study how data-sharing can increase platform market power and reduce seller entry. Our primary contribution is to model tying, a key feature of platforms' strategic behavior, and to use a dynamic general equilibrium model to show how 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.[8] Our model formalizes Cabral (2021)'s argument that merger policy is a blunt tool to address competition in digital industries. Kaplow

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

[5]Endogenous growth models where some products are complementary include Casal (2025) and Feijoo-Moreira (2023); neither paper models acquisitions or platforms.

[6]See Rochet and Tirole (2003), Chen (2024), Brynjolfsson, Chen, and Gao (2025), and Alvarez et al. (2025).

[7]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).

[8]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 and Phillips 2024).

(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. The acquisition of smaller firms by the digital platform can be viewed as a form of vertical integration. Traditionally, vertical integration is analyzed in a static framework and the negative impacts are foreclosures of competitors (Riordan 1998). Empirical analysis based on the static view finds small negative impacts of vertical integrations (Lafontaine and Slade 2007). We show that the harm of such integration can potentially be larger with a long-run growth view because the entry margin is also affected.

Beyond merger policy, Evans and Schmalensee (2014) summarize antitrust issues, including tying, in platform-based markets.[9] Gutiérrez (2023) offers a study of Amazon's fee structure and analyzes the welfare effects of separating its retail and platform businesses. Several papers study interoperability and fee design between different platforms.[10] Madsen and Vellodi (2025) analyze the innovation effects of regulating data-sharing when platforms can imitate third-party sellers. While we abstract from many of these interesting issues in service of parsimony in our baseline model, we bridge the gap between this literature and the growth literature by incorporating platform tying into a growth model. We show how our model can be extended to consider platforms' fee design and competition among platforms in Section 7.

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 with consumption through a platform, we provide evidence that such consumption is becoming an important share of overall economic activity. More details on the data are provided in Appendix A.1.

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

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

Cross Industry Acquisitions. The SDC Platinum Database records all M&A deals over $1 million involving U.S. firms from 1990 onwards. Information on each deal includes the acquirer name, target name, deal value (if known), industry classification and some financial information for publicly listed parties.[11] We focus on GAFAM, motivated by the proposed acquisition bans for these particular firms, but compare the statistics for GAFAM to the same statistics for other large acquirers as a benchmark. The sample period is 2010-2022.

Most GAFAM acquisitions are cross industry, regardless of the specific way we define an industry (Table 1, column 1). In the most conservative definition, based on SDC Platinum's industry classifications, 69% of acquisitions are cross-industry. Applying the 6-digit NAICS classification yields 83%.[12] Comparing GAFAM to other large acquirers, they are *more* likely than others 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 2022; Jin, Leccese, and Wagman 2024). Platform firms are also much more likely to acquire purely "B2C" firms (final goods producers). Prominent examples of cross industry acquisitions include Google's acquisition of FitBit, Amazon's acquisitions of Whole Foods and MGM Studios, and Microsoft's acquisition of LinkedIn.

Platform acquisitions span a wide range of industries. The industries in which GAFAM completed at least one acquisition between 2010 and 2022 accounted for 55% of total U.S. real value added in 2022. In terms of growth, these industries recorded an average annual growth rate of about 3% between 2010-2019, compared with 2.2% for the economy as a whole.[13]

[11] 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. Appendix Table A.1 provides summary statistics about platform firms' acquisitions and contrasts them with deal and target characteristics for other large acquirers.

[12] Weighting transactions by deal value to get a sense of cross-industry deal volume, the corresponding cross-industry shares are 70% and 50%, but the SDC reports deal values for fewer than one third of the observations so we prefer transaction counts.

[13] Over the 2010–2019 sample period, the average annual growth rates of industries targeted by the top 25 Tech, top 25 PE, and top 25 S&P acquirers were 2.4%, 2.17%, and 2.14%, respectively.

	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 target have different industry codes. "GAFAM": Google, Apple, Facebook, Amazon, and Microsoft. Other groups are constructed following Jin, Leccese, and Wagman (2024): the 25 largest non-GAFAM acquirers in Forbes' ranking of Top 100 Digital Companies ("Top 25 Tech"), the 25 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, 2010-2022 and Jin, Leccese, and Wagman (2024) for B2C targets data.

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 platforms 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 account for about 10% of total private final consumption expenditure. 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.[14]

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,

[14]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 (Boppart et al. 2024). The GAFAM firms are all in 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.

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 baseline economy consists of a growing mass of products whose consumption by households is intermediated by a platform. An online retail platform like Amazon is the most natural example. Other examples include the app stores of Apple, Microsoft and Google, the integration of third party apps into Facebook's platform alongside Facebook-owned apps like Instagram and WhatsApp. Some products are produced by the platform itself (e.g. Amazon Basics, Apple Apps) 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. The quantitative model embeds this digital economy into a two sector model alongside a non-digital sector, but we focus here on the dynamics of the digital sector to highlight our new mechanism.

3.1 Environment

Household. A representative household supplies L_t total units of labor and derives utility from real consumption C_t. Its 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. 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, 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 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,[15] represented by δ_t. When there is no tying ($\delta_t = 0$), the platform technology is fully shared with startups and the goods are 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 2020), or reducing the performance of third-party apps on the platform (Department of Justice 2024). Section 7.2 considers an alternative assumption that the platform sells its technology as a service to startups and faces a cost of providing these services, relaxing the assumption that sharing the platform's technology is costless. Similar strategic incentives arise in that alternative model.

[15] 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.

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.[16] At $t = 0$, the economy starts with $N_0 > 0$ products.

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*.[17] 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 startup bargaining power β. When the platform engages in 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 the acquisition rate μ to zero by blocking all 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 all goods (e.g., having a wide range of products from clothing to electronics to video streaming). Ecosystem dominance grows through acquisitions but shrinks as new startups are founded.

[16] An extension with productivity shocks and endogenous exit is developed in Section 7.3.

[17] The term 'startup' is a slight misnomer since it refers to any firm not yet acquired by the platform, including older firms. We use 'startups' as a shorthand for third party sellers and to evoke the digital sector.

Discussion. Before characterizing the equilibrium, we discuss the economic content of the model's new ingredients. First, the platform increases a 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 baseline model has only one platform, this platform faces competition from the substitution of consumption between platform products and startup products, and household substitution between platform use and leisure. The extension in Section 7.1 explicitly models competition between platforms and the predictions of this richer model are qualitatively similar, though competition dampens tying.

Third, Section 7.2 considers the problem of competing platforms to choose fees rather than set tying directly. A platform's optimal fee structure looks similar to the revenue sharing agreements of Google and Apple in their app stores and Amazon's fee structure (Gutiérrez 2023). The revenue share captured by each platform is decreasing in the number of competing platforms. These fees introduce a similar wedge, increasing in ecosystem dominance, as tying does in our baseline model.

Finally, we abstract from within industry acquisitions. A feasible extension, though one we do not pursue here, is for some acquisitions to result in exit of the acquired firm to capture the killer acquisitions channel, and doing so could help match the high acquisition premium we observe in the data.

3.2 Equilibrium

This section first solves the pricing equilibrium to obtain firm profits taking platform use and tying as given, then solves 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 analyzes 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. The quantitative version of model assumes the platform prices its products jointly and simultaneously chooses tying, leading the platform to charge a variable markup and creating an additional distortion from ecosystem dominance. Our focus is on the growth effects of platform mergers rather than static distortions, so we assume constant markups in the baseline model for tractability.[18]

A standard argument then 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 is

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

Two terms in the price index, 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 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 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

[18] Quantitatively, an acquisition ban reduces the markup distortion but this is outweighed in welfare terms by the ban's negative effect on growth (Table 4).

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 and given by:

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

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

In (7) and (8), $\frac{1}{\sigma}$ is the profit margin. In Romer (1990), total profits for all firms are also $\frac{1}{\sigma}$ because all firms have one unit of revenue. In the present model 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 value of ecosystem dominance, so that $\pi_{P,t} > \frac{1}{\sigma} > \pi_{S,t}$. By lowering the quality of startup products, the platform gains an advantage for its own products. This strategic incentive introduces novel implications for growth.

Platform Time Use. The household takes tying and prices as given and chooses how much time to spend using the platform. The household faces a trade-off between leisure time and higher real consumption. The household's problem can be written

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

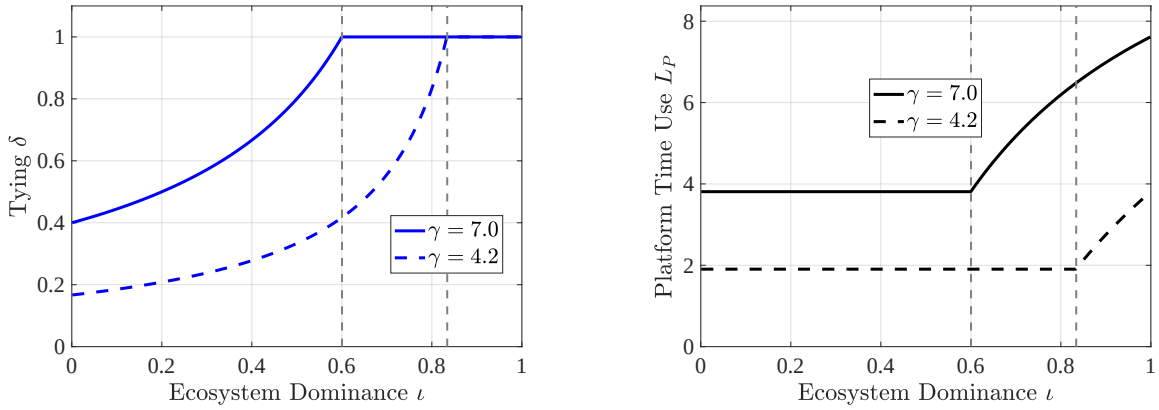
s.t.

$$\text{equation (6)}.$$

The solution is

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

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 ι_t.



(a) Tying **(b)** Platform Time Use

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

Note: Platform tying and household platform time use as functions of the platform's ecosystem dominance for different values of the platform technology parameter γ. σ is set to 4. Vertical lines indicate where maximal tying is reached.

Tying. The platform is the Stackelberg leader and chooses tying to maximize profits (7) taking into account the effect of tying on household platform use (10).[19] This introduces the key tradeoff: tying increases the relative attractiveness of the platform's own products, but reduces household platform use, depressing demand for all goods sold on the platform. Optimal tying 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 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 $\delta = 0$. As the platform 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

[19] Appendix B.2 considers an alternative assumption that the platform takes into account tying's effect on the acquisition market and the entry rate. We show that both of these margins increase desired tying. We focus here on the case of the static profit-maximization because we find it the most realistic and for tractability, similar to how many growth models assume a static pricing game despite the potential effect of prices on entry or innovation effort by rivals. Appendix B.2 also presents the value function of the platform (Equation (29)).

reached faster when the platform technology γ is better. Given ι_t the platform ties (weakly) more when γ is higher.

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: first, holding tying fixed, greater ecosystem dominance has 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 mapping from data on platform time use to the platform technology parameter γ: more platform time use suggests the technology is better.

Finally, given tying and platform use, Figure 2 shows firm profits (equations (7) and (8)). Startup profits fall as ecosystem dominance rises because tying is increasing in ecosystem dominance.[20]

Dynamic Equilibrium. The entry rate (equivalently the growth rate g_t) depends on the forward-looking value of a startup and the forward-looking value of a platform product line because the latter determines the surplus created from acquisitions. As the economy grows, the revenue and profits of each product line fall at rate $g(t)$ as demand is spread over more goods. Denote the detrended value of a platform product v_{Pt} and that of a startup v_{St}. The levels of firm values at t are $\tilde{v}_{Pt} = \frac{v_{Pt}}{N_t}$ and $\frac{v_{St}}{N_t}$, where

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

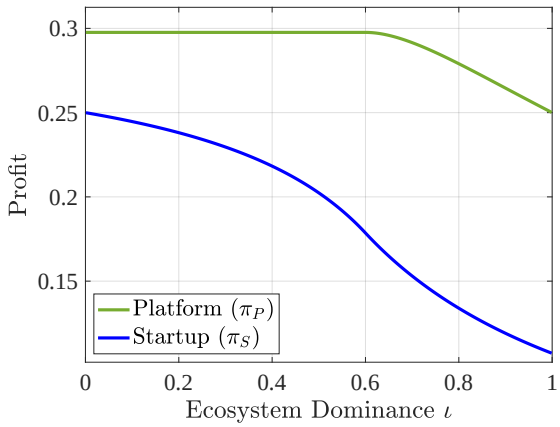


Figure 2: Startup Profits Decline in Ecosystem Dominance

Note: Startup and platform profits as functions of the platform's ecosystem dominance ι. Parameters are set as $\gamma = 7$ and $\sigma = 4$.

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

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.3. 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 the *option value of acquisition*. The startup meets the platform for acquisition at rate μ and 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:

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

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 ι_t evolves according to the 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 growth 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)

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

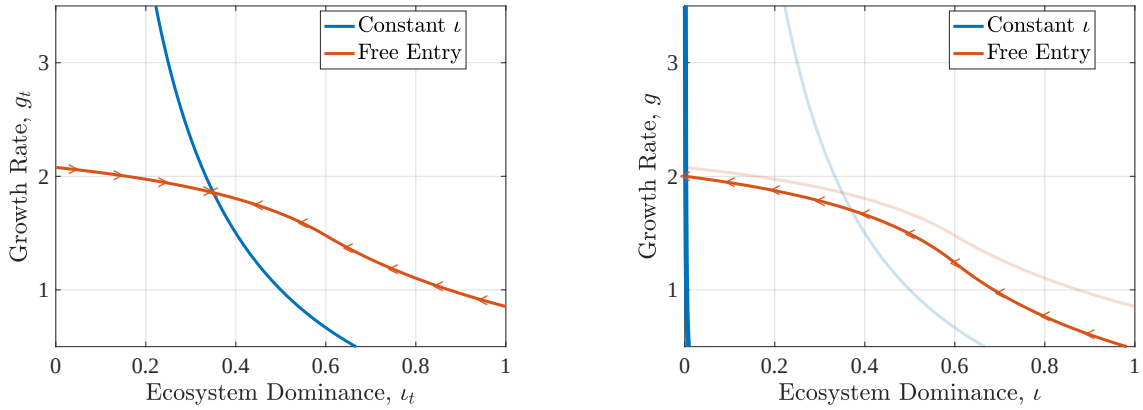
(Labor)

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

Equation (17) tallies labor used in 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 constants, denoted ι^* and g^*. Given ecosystem dominance ι^*, the BGP



(a) BGP with Acquisitions

(b) BGP without Acquisitions

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

Note: The blue curve plots the combinations of (ι, g) such that $\dot{\iota} = 0$, and the red curve plots the combinations of (ι, g) such that the free-entry condition holds. Panel (a) sets the acquisition rate $\mu = 0.03$ 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: $\rho = 0.02, \gamma = 7, \beta = 0.5, \sigma = 4, \kappa = 3.125, \eta = 0$.

growth rate must be consistent with the free-entry condition:

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

Given the growth rate, ecosystem dominance must also be 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 the growth rate: higher ecosystem dominance leads to more tying and lower profits for the startups, discouraging 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 (ι^*, g^*) is the intersection of the two.

4 Effect of An Acquisition Ban on Growth

Returning to the paper's central question: 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.6 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 steady state with acquisitions to one without acquisitions if entry costs are constant (that is, $\eta = 0$) as in Romer (1990).

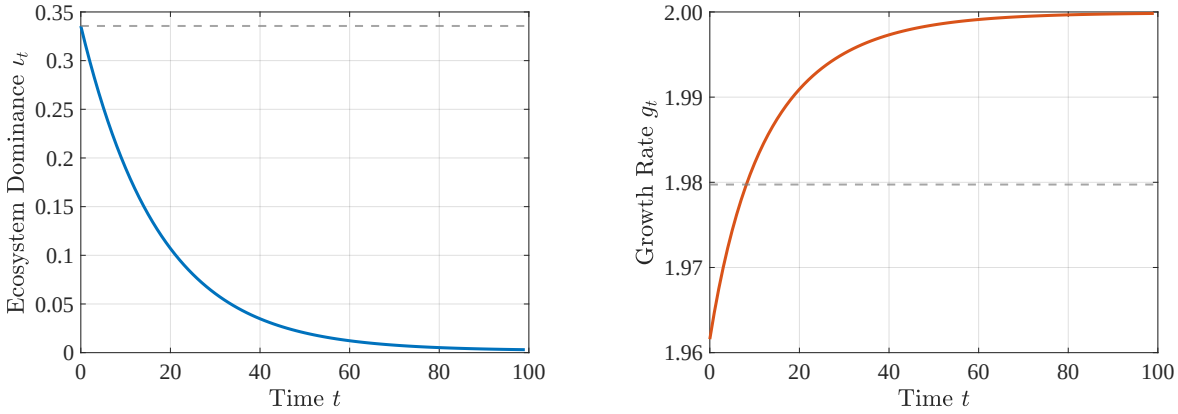
Suppose the economy is in a balanced growth path equilibrium (ι_o^*, g_o^*) with acquisition rate $\mu > 0$. At time 0, the government bans platform acquisitions, setting $\mu = 0$. Given this policy, the platform's ecosystem dominance decays at rate g_t starting from the "old" ecosystem dominance $\iota_0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

Startups' option value of acquisition becomes zero due to the policy so that their value 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.4. 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.



(a) Ecosystem Dominance **(b)** Growth Rate

Figure 4: Transition Path After An Acquisition Ban

Note: 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 each variable. The same parameters as in Figure 3 are used.

Figure 3b depicts the intuition graphically: from the initial steady state with acquisitions in panel 3a, the acquisition ban equilibrium 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 left along the free entry curve with growth increasing from g_0 towards the new steady state. Figure 4 plots the time paths. In this example, the acquisition ban increases the growth rate in the long run. Lemma 3 derives a condition for that 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*

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

The proof is in Appendix B.5. Lemma 3 links the effect of an acquisition ban on the long run growth rate to several objects, potentially measurable in the data.[21]

[21]The challenge with actually measuring these objects in the SDC data is the lack of pre-acquisition valuations and other financial information for target firms, since only six out of the hundreds of targets

The first is the "M&A Premium" which is the value paid by the platform to acquire the startup above the pre-acquisition value of the startup.[22] 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 target's share of the surplus. 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.

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.)

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 solve for the efficient allocation to highlight various distortions in the competitive equilibrium, and then return to analyzing 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

in our sample were public at the time of acquisition.

[22] Table A.1 reports the premium for deals with publicly listed targets. Platforms' average premium was 83%, higher than the 46% for other large firms, but 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%).

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.

Secondly, define a measure of aggregate labor productivity:

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

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 real consumption is 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 on welfare 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.

$$\text{Equation (2), (16), (17),}$$

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

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

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.7 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), tying results in under-utilization of the platform by households in the competitive equilib-

rium, so the planner fully internalizes the productivity effects of household time on the platform and chooses household time use that is twice as high as in the competitive equilibrium.[24] Tying not only affects the static allocation but also impacts the growth rate; contrasting the free entry condition (15) with 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.[25]

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 (Discounted Welfare Effect of an Acquisition Ban)**.** *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:*

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

[24] Our model does not feature the standard network effect externality of household platform use that generates under-utilization of the platform, since the representative household understands its effect on the price index. It would be possible to extend the model in this direction.

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

The proof is in Appendix B.8. 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 tying, but this is achieved by lowering ecosystem dominance and the two exactly offset. An acquisition ban therefore only improves welfare if it increases long run growth. Even in that case, policymakers must trade off the benefit of higher long run growth against the cost of initially lower growth using the household discount rate ρ.

6 Quantitative Model

Before bringing the model to the data, we extend it to include a non-digital sector and allow for variable markups. We then calibrate the extended model, explore the short and long run effects of competition policies, and discuss the sensitivity of the policy conclusions to parameter choices.

6.1 Two Sector Model

To account for the fact that not all industries are affected by platforms, the quantitative model economy is composed of a digital sector d where products are complementary with the platform's service and a non-digital sector n:

$$C_t = C_{dt}^{\psi} C_{nt}^{1-\psi},\ 0 < \psi < 1, \tag{25}$$

where

$$C_{dt} = \left[\int_0^{N_{dt}} \alpha_{it}^{\frac{1}{\sigma}} c_{it}^{\frac{\sigma-1}{\sigma}} di\right]^{\frac{\sigma}{\sigma-1}},\ \text{and}\ C_{nt} = \left[\int_0^{N_{nt}} c_{it}^{\frac{\sigma-1}{\sigma}} di\right]^{\frac{\sigma}{\sigma-1}}. \tag{26}$$

The household expenditure share on the digital sector is ψ. The two sectors have different entry costs κ_d and κ_n to allow for different steady state growth rates across sectors (Ngai and Pissarides 2007). We defer the details to Appendix B.9 and highlight the key modifications to the baseline results.

First, the aggregate price index is given by $\log \bar{P} = \psi \log P + (1-\psi) \log P_n$, where

P is as defined in (4) and $P_n = \frac{\sigma}{\sigma-1} N_n^{\frac{1}{1-\sigma}}$, where N_n is the number of firms in the non-digital sector. Since the non-digital sector is not affected by the presence of the platform, the growth rate in this sector is determined by the free-entry condition balancing entry costs against profits $\kappa_n g_n^{\eta} = \frac{1-\psi}{\sigma(\rho+g_n)}$.

Second, since digital sector consumption is only part of the household's total consumption, they spend less time using the platform. This lower incentive of households to use the platform reduces optimal tying. With constant markups, the equilibrium tying is

$$\delta = \frac{\gamma\psi - (\sigma-1)}{\gamma\psi + (\sigma-1)} \frac{1}{1-\iota},$$

and the equilibrium platform time use, given the platform's optimal tying, is

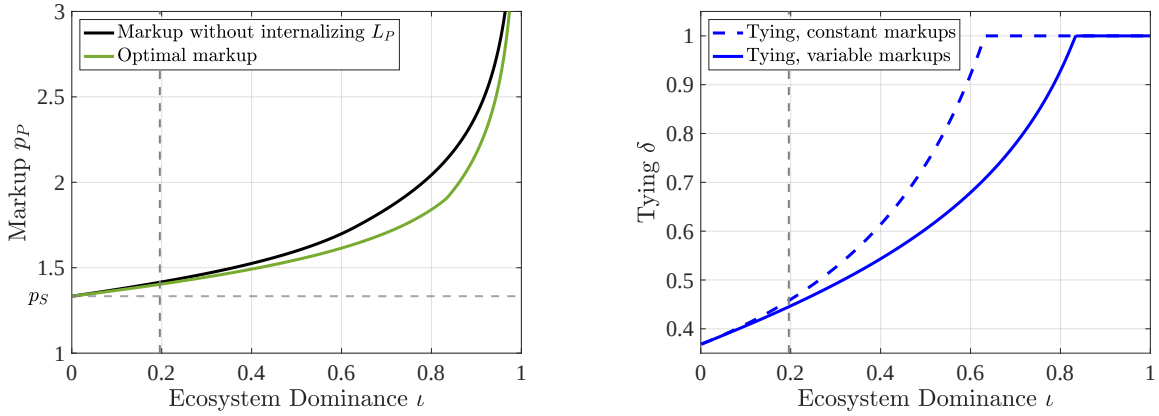
$$L_P = \frac{1}{2}\left(\frac{\psi}{\sigma-1} - \frac{1}{\gamma}\right). \tag{27}$$

Lastly, the welfare incidence of the platform is also dampened. To highlight this, consider the modified welfare decomposition on a BGP:

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

This decomposition resembles the one in the baseline model, with a few modifications to account for the sector shares. The aggregate growth rate is $\bar{g} = \psi g + (1-\psi) g_n$. The utilization index is $\log \bar{P}^u = \psi \log P^u$, since the non-digital sector always has utilization of 1. Correspondingly, the productivity $\log \bar{Z} = \psi \log Z$ since the non-digital sector has productivity of 1. The aggregate entry cost sums the entry costs paid in two sectors: $\bar{K} = \kappa_d g^{\eta+1} + \kappa_n g_n^{\eta+1}$.

Because the digital sector does not have any spillovers to the non-digital sector, an acquisition ban affecting the digital sector has the same qualitative effects on growth and welfare as in the baseline model. Our theoretical results in Sections 4 and 5 stay the same, but the size of the digital sector ψ dictates how much these matter for the overall change in welfare quantitatively.



(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 (black) to the platform's markup with endogenous platform time use (green). The horizontal dashed line is the startups' markup. The vertical dashed line is calibrated ecosystem dominance. Panel (b) compares platform tying in the baseline model with constant markups to platform tying with variable markups and simultaneous choice of prices and tying. Parameters in Table 2.

6.2 Variable Markups

Relaxing the assumption that the platform does not choose prices for its goods jointly yields a symmetric problem for the platform to choose prices and tying:

$$\begin{aligned} \max_{p_P,\delta\in[0,1]} \quad & \pi_P = (p_P - 1)\,(1 + L_P\gamma)\left(\frac{p_P}{P}\right)^{-\sigma}\frac{\psi}{P} \\ \text{s.t.} \quad & L_P = \left(\frac{\psi}{\sigma-1} - \frac{1}{\gamma}\frac{\iota p_P^{1-\sigma} + (1-\iota)p_S^{1-\sigma}}{\iota p_P^{1-\sigma} + (1-\iota)\,(1-\delta)\,p_S^{1-\sigma}}\right) \\ \text{and} \quad & P = N^{\frac{1}{1-\sigma}}\left(\iota(1+L_P\gamma)p_P^{1-\sigma} + (1-\iota)(1+L_P\gamma\,(1-\delta))p_S^{1-\sigma}\right)^{\frac{1}{1-\sigma}}. \end{aligned} \tag{28}$$

The solution for the price, derived in Appendix B.10, 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 with the platform's markup on each of its products increasing in its market share (Atkeson and Burstein 2008), except that the relevant market share $\tilde{s}_P$ is less than the sales share s_P so the chosen markup is lower. The

platform internalizes the negative effect of its prices and tying on household time use and thus overall demand. This downward adjustment to the markup is small in the calibrated model, especially for low levels of ecosystem dominance (Figure 5a). When the platform can adjust prices and tying together, desired tying is also slightly lower for the same level of ecosystem dominance than in the baseline model (Figure 5b).

6.3 Calibration

The calibration proceeds in four steps. The resulting parameter values are summarized in Table 2. First, standard preference parameters are taken from the literature, with $\rho = 0.02$ 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 follow Acemoglu et al. (2018) in setting the curvature of the entry cost $\eta = 1$. The target's (startup's) bargaining power β is set to 0.5 (David 2020) but we explore sensitivity of the results to this choice since the option value of acquisition is a key force in the model. We count industries as digital if they experienced at least one platform acquisition since 2010, and use the 55% share of GDP of these industries to set $\psi = 0.55$.[26]

The second step calibrates the entry costs to match the sectoral growth rates reported in Section 2. This calibration assumes the platform's technology $\gamma = 0$ and $\mu = 0$ so that the growth rate in this "pre-platform" steady state is driven purely by the balance between startup profits and entry costs and the free entry curve in the digital sector is $\kappa_d g^\eta = \frac{\psi}{\sigma(\rho+g)}$.

Third, conditional on the choices of σ and ψ, household platform time use in the data implies a value of the platform technology parameter γ. We target two hours of platform time use per day, the midpoint of the survey estimates in Section 2. Given the uncertainty around how much time is spent engaging in the activities our model captures, as well as γ's role in governing the response of startup profits

[26]Choosing a lower value for the size of the digital sector, such as Amazon's 40% share of e-commerce, implies a a smaller welfare loss from an acquisition ban of around 0.1%.

	Value	Meaning	Source/Target
Panel A: Externally calibrated parameters			
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: Internally calibrated parameters			
ψ	0.55	Digital sector expenditure share	GDP share, digital sector
κ_d	14	Entry cost, digital sector	Growth rate, digital sector
κ_n	54	Entry cost, non-digital sector	Growth rate, non-digital sector
γ	11.81	Platform technology	Platform time use
μ	0.0221	Merger meeting rate	Platform revenue share

Table 2: Parameter values, baseline.

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 with $\gamma = 11.81$. The calibrated value implies steady state ecosystem dominance of 19.6%. The implied acquisition rate is 2.2%. Assessing how realistic this is depends on the choice of the population of potential target firms. In total, GAFAM have acquired around 700 firms since 2010. This is quite low relative to the total population of firms in the industries where they acquired. On the other hand many of those are small firms that may never have been considered as potential targets. Overall we find a 2% annual chance of acquisition reasonable.

Table 3 demonstrates the exact model fit of the data for the pre-platform and platform steady states. The parameters imply tying of 45%, meaning 55% of the platform's appeal is shared with startups. The middle panel reports the steady state welfare gain from the introduction of the platform into the economy. Households generate significant real consumption benefits by using the platform and the presence of the platform induces a slightly higher growth rate. These outweigh the increase in the markup distortion. The bottom panel reports the welfare gain from the pre-platform equilibrium over the transition to the platform equilibrium. The majority of the welfare changes occur immediately through platform utilization so the steady state comparison and welfare over the transition are very similar.

	Data	Pre-platform	Platform
Panel A: Model fit for targeted moments			
Growth rate, %	2.200	2.200	2.210
Platform time use, hours/day	2.0	0	2.0
Platform revenue share, %	11	0	11
Tying δ, %	-	0	45
Panel B: Steady state welfare comparison			
Welfare, CE % chg.	-	-	0.96
Growth	-	-	0.25
Platform	-	-	0.89
Markup	-	-	-0.18
Panel C: Welfare over the transition			
Discounted Welfare, CE % chg.	-	-	0.96

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.

6.4 Policy Experiments

Acquisition Ban. An acquisition ban removes the option value of acquisition and reduces the growth rate to its pre-platform steady state level, resulting in a steady state welfare loss of 0.15% (Table 4). The growth rate over the transition falls even more, so the relevant decline over the transition is larger: 0.21%. The sensitivity analysis (Section 6.5) reveals that the negative effect of an acquisition ban is fairly robust to alternative calibrations.

Tying Ban. A tying ban provides large and immediate welfare benefits. It eliminates differences in profits for the platform and standalone firms, increasing the long run growth rate. The bulk of the gains, however, come from eliminating platform under-utilization. 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. 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

	Base.	Acq. Ban	Tying Ban	First Best
Panel A: Model fit for targeted moments				
Growth rate, %	2.210	2.200	2.224	3.795
Platform time use, hours/day	2.0	2.0	3.9	3.9
Platform revenue share, %	11	0	9	6
Tying δ, %	45	37	0	0
Panel B: Steady state welfare comparison				
Welfare, CE % chg.	-	-0.15	3.79	28.61
Growth	-	-0.25	0.36	21.26
Platform	-	-0.08	3.41	3.41
Markup	-	0.18	0.03	3.95
Panel C: Welfare over the transition				
Discounted Welfare, CE % chg.	-	-0.21	3.79	24.98

Table 4: Features of the equilibrium 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 details on welfare components.

in search, reduced Amazon's self-preferencing from 30 ranks to 20, for example.

6.5 Sensitivity Analysis for Acquisition Ban Results

Startup Bargaining Power β. We vary startup bargaining power β between 0 and 1 with all other parameters held at their baseline values from Table 2 and compute a new equilibrium for each value of β. The top left panel of Figure 6 shows the merger premium (defined in Lemma 3) 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 costs of an acquisition ban are larger when startup bargaining power is high, and a ban increases welfare if β is sufficiently low (around $\beta = 0.2$). This is because the option value of acquisition does not provide a significant entry motive in the pre-ban steady state when β is low. For all possible values of β the merger premium in the calibrated model is low, at most 15%, compared to the 47% average premium in the data found by David (2020), who includes all acquisitions of public firms, and our Table A.1 that focuses on the largest acquirers and finds premia between 45-83% depending on the acquirer type, with platforms having a premium of 83% but based on only six deals,

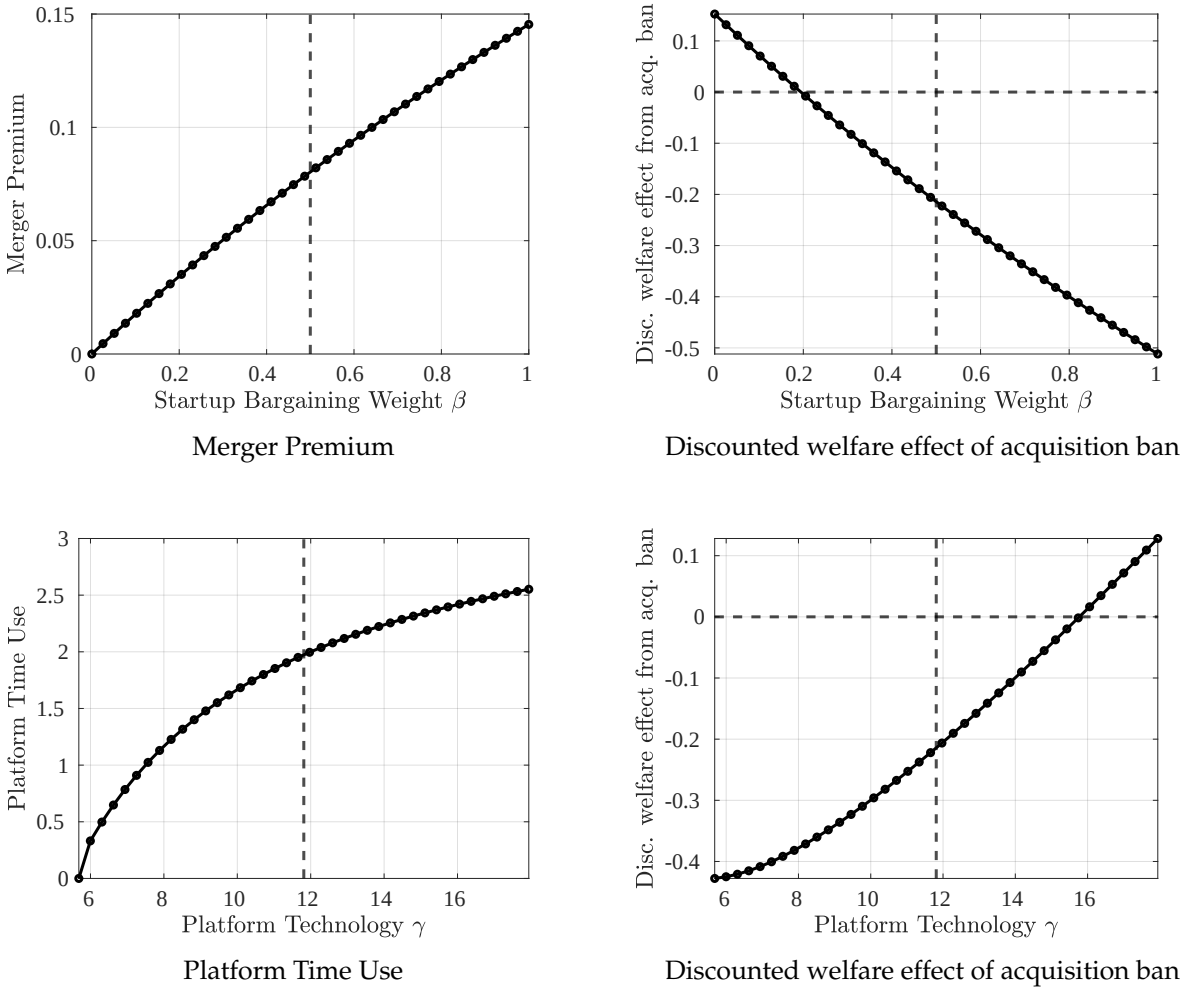


Figure 6: Welfare Effects of An Acquisition Ban Under Alternative Calibrations
Note: Sensitivity analysis of the welfare effects of an acquisition ban to changes in the startup bargaining power β (top panel) and the platform technology γ (bottom panel). The vertical dashed lines indicate the baseline value of each parameter. Other parameter values in Table 2.

so we did not feel comfortable calibrating the model directly to this target. The low premium in our model relative to the data suggests that we may be understating the costs of an acquisition ban.

Platform Technology γ. We next explore alternative values of γ, each one associated with a different value of platform time use. Varying the platform technology affects the platform's revenue share, so for each value of γ, μ is re-calibrated to match the 11% revenue share target. The results are in the bottom panel of Figure 6. When γ is high, an acquisition ban increases welfare because there is a larger

response of startup profits, consistent with Lemma 3. If a higher platform time use target of 2.5 hours per day instead of 2 were used to estimate γ, for example, the estimated welfare gains from an acquisition ban would be slightly positive.

7 Model Extensions

The theoretical framework can accommodate other extensions that capture important features of platform-based industries. We briefly describe three such extensions of the baseline model, leaving the details to Appendix C for brevity.

7.1 Competition Between Platforms

A central defense of platform firms in antitrust cases is the fierce competition between different platforms (OECD 2023). Appendix C.1 describes a version of the model with two platforms, j and k, with heterogeneous technologies γ_j and γ_k. The platforms' technologies are perfect substitutes from the perspective of households and both platforms make a tying decision. Similar to limit pricing with Bertrand competition, the presence of a second platform constrains the tying behavior of the leading-technology platform j, requiring

$$\delta_{jt}^* \leq \left(\frac{\gamma_j}{\gamma_k} - 1\right) \frac{1}{1-\iota_j}.$$

Greater ecosystem dominance ι_j relaxes this constraint, as does a larger technology gap $\frac{\gamma_j}{\gamma_k}$ between j and k. Figure C.1 shows the tying solution and the welfare effects of an acquisition ban under different technology gaps between rivals. When the rival platform's technology approaches that of the leading platform, tying and the welfare effects of an acquisition ban go to zero.

7.2 Market For Platform Services and Revenue Sharing

Appendix C.2 describes a version of the model where the platform sells its services (e.g. sponsored search results) to startups and faces a downward sloping demand curve, either because of diminishing returns to platform services for startups or

because of competition from other platforms. Hence this extension also offers a second way of thinking about competition between platforms where instead of being perfect substitutes the elasticity of substitution between different platforms is one. See C.2.1 for further discussion. The platform chooses a price for its services that is even higher than the usual monopolist markup in order to depress startups' demand for platform services and boost its own sales. This generates a similar wedge in quality between its products and startups' products as the tying choice in the baseline model (Lemma 6 and Figure C.2). Startups' payments to the platform in this extension resemble the revenue-sharing arrangements that are common for online retailers like Amazon (Gutiérrez 2023). The revenue share taken by the platform is decreasing in the number of competing platforms (Equation 39 and Section C.2.1).

7.3 Quality-Based Theories of Harm

Appendix C.3 develops a final extension that addresses quality-based theories of harm for platform mergers (OECD 2023). In this extension, firms' labor productivities evolve stochastically and they pay fixed operating costs so that they exit when productivity is low. Consistent with quality-based theories of harm, tying lowers the exit threshold for the platform and raises it for startups, implying that the platform has lower quality products on average. The wedge between startups' exit threshold and the platform's is increasing in ecosystem dominance.

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 engage in activities that reduce demand for third party sellers' products in favor of its own. Quantitatively we find that regulations targeted at these other activities matter much more for welfare than stricter acquisition policy, and that an acquisition ban would reduce welfare. An interesting direction for future research is to consider how competition policy affects the incentives of platforms to improve the platform technologies themselves and introduce their own new products.

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Supplemental Appendix

A Supplemental 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, more than the other three groups of large acquirers, giving us 665 total deals for this group.[27] In terms of cross-industry acqui-

[27] 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			
Average 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
Age - Ind Avg. Age	-4.0	0.4	9.1	4.8
Employees	4582	9020	1978	376
Emp.-Ind Avg. Emp.	879.7	1380.9	1928.4	305.3
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, 2010-2022, 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 (2022): 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.

sitions, 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 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: Random Search with Heterogeneous Firms

One concern is that platforms where startups sell their products may not meet startups at random. If platforms acquire only high quality startups it could change the predictions of the model. To investigate this, 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.[28] 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), and 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 $n_i = \sum_{k=1}^{132} n_{i,CPC_k}$. The controls are also required to have the 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.

[28] 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 Supplemental 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 Dynamic Tying Decision and Tying's Effect on the Acquisition Market

This section considers an alternative assumption about decision-making where the platform internalizes all of the effects of tying, including its dynamic effect on entry and the acquisition price of target firms in the acquisition market. We show that (i) the platform's total value is independent of the number of varieties N, (ii) with attention to the acquisition market the platform has higher desired tying, and (iii) with attention to the growth rate the platform has higher desired tying.

To characterize the tying decision, we start by writing the total value V of the platform as a function of the two relevant states: ecosystem dominance ι and the number of varieties, N, on a balanced growth path:

$$\rho V(\iota, N) = \max_{\delta} N\frac{\pi_P}{N}\iota + (1-\beta)\mu(1-\iota)\left(V_\iota(\iota, N) - N\tilde{v}_S\right) - g\iota V_\iota(\iota, N) + gNV_N(\iota, N), \tag{29}$$

where we denote the value of platform $V(\iota, N)$. The first term is the flow profits from all product lines the platform owns; the second term is the change in ι due to acquisitions; the last terms are the change in ι and N due to entry.

From our derivation of the static profits, π_P is independent of ι when tying is interior (see Figure 2), and the value of a standalone firm is $\tilde{v}_S = \frac{v_S}{N}$. Together, they imply that the value of the platform is only a function of ι, with $V_N(\iota, N) = 0$:

$$\rho V(\iota) = \max_{\delta} \pi_P \iota + (1-\beta)\mu(1-\iota)\left(V'(\iota) - v_S\right) - g\iota V'(\iota). \tag{30}$$

Intuitively the platform's value is independent of the number of varieties because profits per product line fall with additional products because of the CES demand system. Now taking the first-order condition with respect to δ:

$$0 = \frac{\partial \pi_P}{\partial \delta} + \frac{\partial \pi_P}{\partial L_P}\frac{\partial L_P}{\partial \delta} - (1-\beta)\mu(1-\iota)\frac{dv_S}{d\delta} - \iota V'(\iota)\frac{dg}{d\delta}. \tag{31}$$

In equation (31), the first two terms capture the same static tradeoffs faced by the platform as in the baseline model, while the last two terms capture the acquisition market and growth rate considerations respectively. Because $\frac{dv_S}{d\delta} < 0$ (tying reduces the value of startups), accounting for the effect on the acquisition market increases tying to reduce the acquisition price the platform pays for startups. Similarly, in terms of dynamic considerations, faster growth erodes ecosystem dominance. Tying reduces the growth rate ($\frac{dg}{d\delta} < 0$) which suggests a dynamic benefit to additional tying. Together, these two forces would lead the platform to choose higher tying than in the baseline model for the same level of ecosystem dominance.

B.3 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.4 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.5 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.6 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 5. *A small decrease in μ (stricter acquisition policy) leads to a higher BGP growth rate if*

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

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 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 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. 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.7 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 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

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

B.8 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:

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

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.9 Two Sector Model

We discuss the details of the model with two sectors. The qualitative predictions from the main text stay the same, while the quantitative predictions can change. The digital sector has the same price index as in the baseline model. In the non-digital sector, because all firms are infinitesimal, they price at a constant markup $\frac{\sigma}{\sigma-1}$. The profit for an individual firm in the non-digital sector (following the same definition as in equation (7)) is thus $\pi_n=\frac{1-\psi}{\sigma}$ at any moment of time. Correspondingly, the price index of the non-digital sector is

$$P_n=\frac{\sigma}{\sigma-1}N_n^{\frac{1}{1-\sigma}}.$$

where N_n is the number of firms operating in this sector.

With the entry cost being $\kappa(g_n)\frac{1}{N_n}$, the free-entry condition requires that an entering firm breaks even in the non-digital sector, and thus $\kappa(g_n) = \frac{1-\psi}{\sigma(\rho+g_n)}$. Aggregating between the digital and non-digital sectors, we have the price index for the final consumption $\bar{P} = P^{\psi}P_n^{1-\psi}$, where P is the digital-sector price index as developed in the main text. The real consumption of the household is thus $C = P^{-1}$.

With the price indices in hand, we solve the household's platform usage problem:

$$\max_{L_P} \; -(\psi \log P + (1-\psi)\log P_n) - L_P.$$

s.t.

$$\text{equation (6)}.$$

Note that in this problem, the price index of the non-digital sector is irrelevant. Taking a similar first-order condition as in the main text, we reach the optimal usage of the household as

$$L_P = \frac{\psi}{\sigma - 1} - \frac{1}{\gamma(\iota + (1-\iota)(1-\delta)},$$

where we focus on the non-zero platform usage case. The platform takes as given this relationship between usage and tying and maximizes the following problem:

$$\max_{\delta} \quad \frac{\psi}{\sigma}\frac{1+\gamma L_P}{1+\gamma L_P(\iota + (1-\iota)(1-\delta))}.$$

The optimal tying solution and the corresponding time usage is in the main text, where

$$\delta^* = \frac{\gamma\psi - (\sigma-1)}{\gamma\psi + (\sigma-1)}\frac{1}{1-\iota},$$

and

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

Given these endogenous variables, we follow a similar decomposition of the house-

hold's discounted utility on a balanced growth path:

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

B.10 Variable Markups

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 (28) of choosing tying and prices are (we ignore ψ in these conditions because it enters multiplicatively in all terms):

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

$$FOC_{\delta} \quad \left[\frac{\frac{\partial \alpha_P}{\partial \delta}}{\alpha_P} - \frac{\frac{\partial \alpha_S}{\partial \delta}}{\alpha_S}\right] + \left[\frac{(\sigma-1)}{p_P}\frac{s_P}{1-s_P}\right] = 0 \tag{33}$$

$$\text{where} \quad s_P \equiv \frac{\iota \alpha_P p_P^{1-\sigma}}{\left(\iota \alpha_P p_P^{1-\sigma} + (1-\iota)\alpha_S p_S^{1-\sigma}\right)} \text{ is the platform's market share.} \tag{34}$$

The first term in (32) 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 single product 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.

C Supplemental Model Extensions Appendix

C.1 Extension 1: Competition Between Platforms

Consider an economy with two platforms, j and k, with technologies γ_j and γ_k, respectively. Let ι_j denote j's share of products in the economy and ι_k denote k's share. Each platform makes a tying decision. Product qualities α_i are given by

$$\begin{aligned}
\alpha_S &= 1 + \gamma_j L_{Pj}(1-\delta_j) + \gamma_k L_{Pk}(1-\delta_k), \\
\alpha_j &= 1 + \gamma_j L_{Pj} + \gamma_k L_{Pk}(1-\delta_k), \\
\alpha_k &= 1 + \gamma_j L_{Pj}(1-\delta_j) + \gamma_k L_{Pk}.
\end{aligned}$$

The price index can be written

$$\begin{aligned}
P_t = \frac{\sigma}{\sigma-1}\Bigg(N_t\Bigg(1 + (1-\iota_j-\iota_k)(\gamma_j L_{Pj}(1-\delta_j) + \gamma_k L_{Pk}(1-\delta_k)) \\
+ \iota_j(\gamma_j L_{Pj} + \gamma_k L_{Pk}(1-\delta_j)) + \iota_k(\gamma_j L_{Pj}(1-\delta_j) + \gamma_k L_{Pk})\Bigg)\Bigg)^{\frac{1}{1-\sigma}}.
\end{aligned}$$

Households choose time use on each platform to maximize:

$$\begin{aligned}
\max_{L_{pj}, L_{pk}} \frac{1}{(\sigma-1)} \log(1 + L_{pj}\gamma_j((1-\iota_j-\iota_k)(1-\delta_j) + \iota_j + \iota_k(1-\delta_j)) \\
+ L_{pk}\gamma_k((1-\iota_j-\iota_k)(1-\delta_k) + \iota_j(1-\delta_k) + \iota_k))) - L_{pj} - L_{pk}.
\end{aligned}$$

Because the two platforms are perfect substitutes in the product qualities, L_{pj} and L_{pk} are not separately pinned down. The first order conditions are:

$$\begin{aligned}
\frac{\frac{1}{(\sigma-1)}\gamma_j E_j}{1 + L_{pj}\gamma_j E_j + L_{pk}\gamma_k E_k} &= 1 \\
\frac{(\frac{1}{(\sigma-1)})\gamma_k E_k}{1 + L_{pj}\gamma_j E_j + L_{pk}\gamma_k E_k} &= 1,
\end{aligned}$$

where

$$E_j \equiv ((1-\iota_j-\iota_k)(1-\delta_j)+\iota_j+\iota_k(1-\delta_j)) \tag{35}$$

$$E_k \equiv ((1-\iota_j-\iota_k)(1-\delta_k)+\iota_j(1-\delta_k)+\iota_k)) \tag{36}$$

represent the weights households place on each ecosystem depending on tying and the product shares.

Without loss of generality we focus on the case where $L_{pk}=0$. For households to be willing to only use platform j the first order conditions imply a participation constraint for households that $\gamma_j E_j \geq \gamma_k E_k$. The most competitive that platform k can be to induce households to switch to platform k is to offer $\delta_k = 0$, which implies $E_k = 1$. The maximal tying platform j can choose to satisfy $\gamma_j E_j \geq \gamma_k E_k$ is then given by:

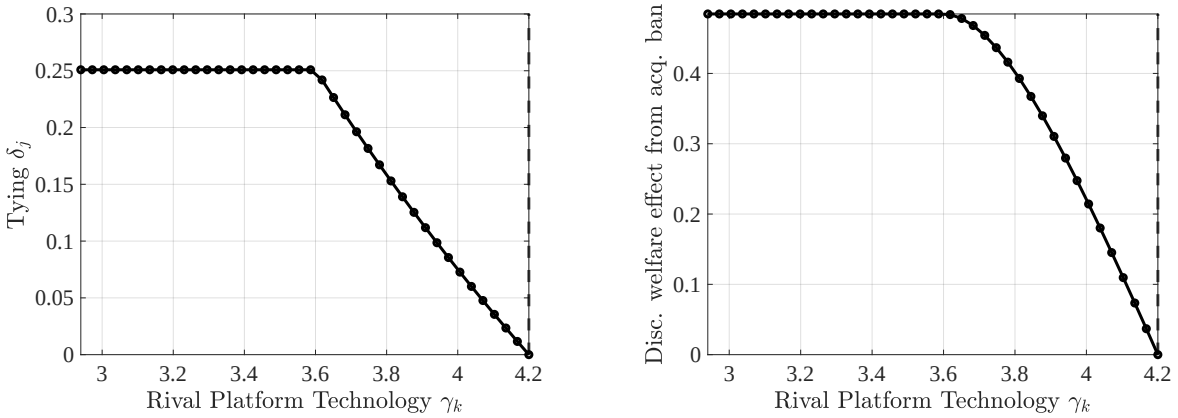
$$\delta_j^{cons} = \left(\frac{\gamma_j}{\gamma_k}-1\right)\frac{1}{1-\iota_j}.$$

Notice that this constraint relaxes as j's ecosystem dominance ι_j increases. Platform j's optimization problem remains the same as in the baseline model with the additional constraint that $\delta_j \leq \delta_j^{cons}$, so the solution is:

$$\delta_{jt}^* = \min\left\{\left(\frac{\gamma_j}{\gamma_k}-1\right)\frac{1}{1-\iota_j}, \frac{\gamma_j-(\sigma-1)}{\gamma_j+(\sigma-1)}\frac{1}{(1-\iota_{jt})}, 1\right\}. \tag{37}$$

Figure C.1a plots platform j's optimal tying in this version of the model as a function of platform k's technology using the same parameterization as in Table 2. For very low values of the platform k's technology, j is unconstrained and picks the same value for tying as in the baseline model. As k's technology increases, tying begins to falls and when platforms' technologies are equal they cannot tie at all, analogous to limit pricing in a Bertrand pricing game.

The rest of the model is the same as in Section 3. Figure C.1b shows the welfare effects of an acquisition ban depending on the toughness of k's competition with j. Competition dampens the welfare effects of an acquisition ban but does not reverse them.



(a) Platform j's tying δ_j **(b)** Discounted welfare effect of acquisition ban

Figure C.1: Welfare Effects of An Acquisition Ban in Platform Competition Model
Note: Sensitivity analysis of the welfare effects of an acquisition ban to the second platform's technology γ_k in the platform competition extension. Other parameters are $\rho = 0.02, \gamma = 4.2, \beta = 0.5, \sigma = 4, \kappa = 3.125, \eta = 0$.

C.2 Extension 2: Market For Platform Services

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

[29]The utilization elasticity can be micro-founded by a model where multiple platforms offer imperfectly substitutable services (see Appendix C.2.1 for details). In this interpretation, ϵ decreases in the number of platforms.

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

$$q = \frac{1}{\sigma} \frac{\epsilon \gamma L_P u_S^{\epsilon-1}}{1+\gamma L_P \left(\iota u_P^\epsilon + (1-\iota) u_S^\epsilon\right)}. \tag{38}$$

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:

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

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. From equation (38), choosing the price q is equivalent to choosing the startups' utilization directly, so the problem can be rewritten as

$$\max_{u_S, u_P} \iota \pi_P + (1-\iota) \frac{\epsilon}{\sigma} \frac{\gamma L_P u_S^\epsilon}{1+\gamma L_P \left(\iota u_P^\epsilon + (1-\iota) u_S^\epsilon\right)} - (\iota u_P + (1-\iota) u_S)\omega. \tag{39}$$

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

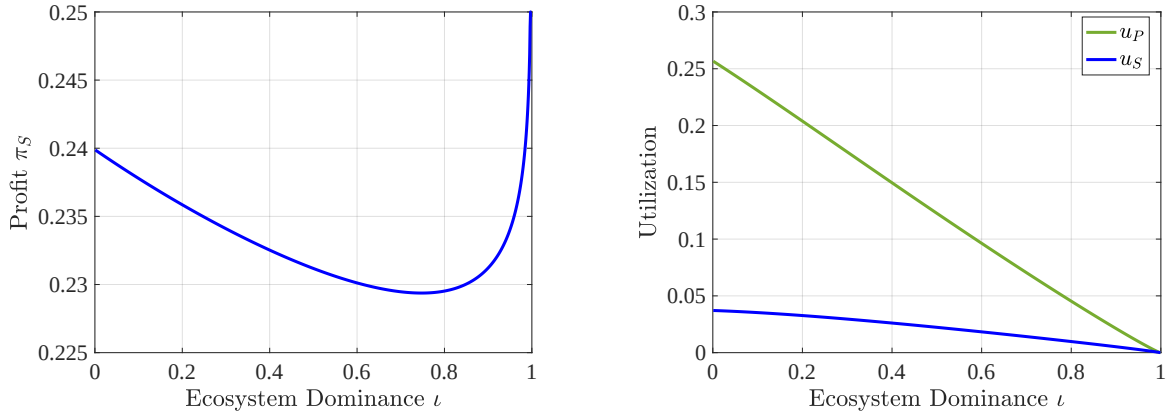
Lemma 6. *Under the platform's optimal choices for utilization:*

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

where

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

The proof is in Appendix C.2.2. Under the optimal utilization choice, $u_S < u_P$,



(a) Startup Profits

(b) Utilization of Platform Services

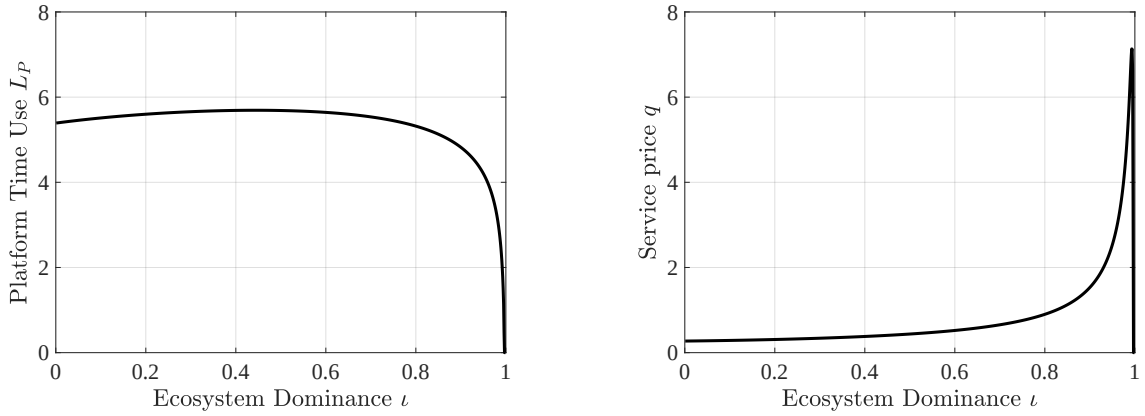
Figure C.2: Startup Profits and Platform Utilization: Revenue Sharing Model

Note: Utilization and startup profits as a function of the platform's ecosystem dominance in the revenue sharing model. Parameters are the same as in Figure 3, plus $\epsilon = 0.1$ and $\omega = 0.05$.

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. Further details are in Appendix C.2.3.

Startup profits initially decline in ecosystem dominance like in the baseline model (Figure C.2a). 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 C.2b). Because the platform always chooses lower utilization for startups, this pushes total utilization down as ecosys-



(a) Platform Time Use **(b)** Platform Service Price q

Figure C.3: 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. Parameters are the same as in Figure 3, plus $\epsilon = 0.1$ and $\omega = 0.05$.

tem dominance grows, causing households to reduce their time on the platform to zero (Figure C.3a). As that happens, startup profits return to $\frac{1}{\sigma}$, hence the eventual rise in profits in Figure C.2a. 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.

C.2.1 Micro-Foundation: 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:

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

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 conditions:

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

Although fully characterizing the equilibrium outcome with multiple strategic platforms requires us to impose additional structure, we note that if we relabel $\epsilon = \frac{1}{J}$, the demand curve from the standalone firms resembles the one considered in the previous section:

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

with $\tilde{L}_j = L_P \Pi_{k\neq j} u_k^{1/J}$. In this version ϵ is related to the competition in the market for platform services: ϵ decreases in the number of platforms.

C.2.2 Proof of Lemma 6

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

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

and

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

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. □

C.2.3 Revenue Sharing With Endogenous Time Use

Proof. 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

$$\max_{u_S,u_P} \ \iota\pi_P + (1-\iota)\frac{\epsilon}{\sigma}\frac{\gamma L_P u_S^\epsilon}{1+\gamma L_P\left(\iota u_P^\epsilon + (1-\iota)u_S^\epsilon\right)} - (\iota u_P + (1-\iota)u_S)\omega. \tag{40}$$

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

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

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. □

C.3 Extension 3: Quality-Based Theories of Harm

This 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 can 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 $\kappa(g_t)$ scales in $A_t N_t$. To generate exit dynamics we assume operating a product line incurs an operating cost of $\frac{\omega}{A_t N_t}$.

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

$$\iota_t = \frac{A_{Pt}}{A_t} \frac{N_{Pt}}{N_t}, \tag{41}$$

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.

[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.

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 (41).

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

$$(\rho + g) v_P(a) = e^a \pi_P - \omega + \frac{\nu^2}{2} v_P''(a). \tag{42}$$

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 (42) reflects the fact that productivity changes over time following the Brownian motion.

Similarly, a startup has the Bellman equation

$$(\rho + g) v_S(a) = e^a \pi_S - \omega + \mu\beta(v_P(a) - v_S(a)) + \frac{\nu^2}{2} v_S''(a). \tag{43}$$

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.

On a balanced growth path, the equilibrium value of firms are given by the following equations, which can be directly verified as the solution to equation (43)

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

and

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

where $\eta_P = \left(\frac{\rho + g}{\nu^2/2} \right)^{1/2}$ and $\eta_S = \left(\frac{\rho + g + \mu\beta}{\nu^2/2} \right)^{1/2}$. The following lemma summarizes the core predictions for the selection on exiting.

Lemma 7 (Exit Threshold)**.** *On a balanced growth path, the exit thresholds are solutions to the following equations*

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

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.