Platform Acquisitions, Ecosystem Dominance, and Growth*

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Abstract

We develop a model of consumption through a platform to understand the growth effects of acquisitions by platform-based firms. The platform supplies some of the products in the economy and startups supply the rest. The platform chooses how much of its appeal to share with the startups (''product tying"), balancing the incentive to increase sales of its own products against the desire to attract users to the platform. The chance to be acquired by the platform provides a motive for startup entry. But acquisitions also expand the platform's product offerings ("ecosystem dominance"), increasing tying and lowering the profits of non-acquired startups which are the other motive for entry. Theoretically, acquisition bans always reduce growth in the short run but may have long-run benefits. The model calibrated to U.S. households' platform time use suggests negligible welfare gains from an acquisition ban.

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1 Introduction

Policymakers are increasingly focused on competition and growth in digital markets. Legislation in the US, UK, and Europe has singled out the acquisitions of the "GAFAM" (Google, Amazon, Facebook, Apple, and Microsoft) firms for additional scrutiny or even bans because of their role as ''gatekeepers" or ''covered platforms." We propose a framework to analyze the special competitive forces of an economy where numerous goods and services are consumed through a platform and the firm operating the platform also sells some of its own products on the platform. This framework builds tractably on the standard constant elasticity of demand system used in macroeconomics, trade, firm dynamics, and beyond.

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 additional incentive for startup founders on top of the profits they expect to generate as a standalone firm, so-called "entry for buyout" (Rasmusen 1988; Fons-Rosen, Roldan-Blanco, and Schmitz 2024). On the other hand, the presence of a dominant "digital ecosystem" with many integrated products and services sold by a platform may make it hard for standalone firms to make profits in the first place (Khan 2017).

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

At the same time, using the platform provides benefits to households, some of which depend on the overall intensity of use of the platform (capturing network effects), and some of which do not (such as reduced search costs). Households take as given the number and quality of products available on the platform and choose how much to use the platform each period.

The platform firm faces a tradeoff when it decides how much to engage in product tying. Tying increases the attractiveness of the platform's products relative to third-party products, thus increasing sales and profits on each product line the platform owns. On the other hand, it discourages households from using the platform alto-

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

gether, which depresses aggregate demand, lowering sales and profits.

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

The first theoretical result is that platform acquisitions have ambiguous effects on entry (and thus growth and welfare). On one hand, the option value of acquisition induces more entry by startups (Rasmusen 1988; Fons-Rosen, Roldan-Blanco, and Schmitz 2024). On the other hand, new to our paper, acquisitions increase tying, lowering startups' standalone value before acquisition and discouraging entry. We derive a condition on parameters such that an acquisition ban has positive long-run effects on growth. Acquisition bans are more likely to be beneficial when the option value of the acquisition is low compared to the responsiveness of standalone profits to ecosystem dominance. These two channels can be directly linked to measurable objects in the data.

The second result is that, even if an acquisition ban increases growth in the long run, it necessarily involves sacrificing growth in the short run because entry for buyout incentives changes immediately while the costs of ecosystem dominance and tying diminish slowly. This leads us to focus on transition paths rather than steady-state comparisons when evaluating the welfare effects of competition policies.

The model has one novel parameter, the platform's appeal, which we calibrate using the model's mapping from this technology parameter to household time spent using the platform, which can be measured in surveys.

In the calibrated model an acquisition ban increases steady state consumption-equivalent welfare by 0.18%. Because a ban reduces entry in the short run, the properly discounted welfare *over the transition* increases by just 0.02%. For slightly higher values of entrant bargaining power, a higher discount rate, or lower values of the platform technology parameter, which all seem plausible, the discounted welfare effect of an acquisition ban is negative. A direct ban on tying implies significantly higher welfare gains, primarily by correcting platform under-utilization in the competitive equilibrium.

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

In an extension with idiosyncratic productivity shocks, the platform induces negative selection. Tying raises the platform's profits on low-productivity products and makes them less likely to be shut down. For startups the opposite occurs: tying increases their exit threshold, meaning that some startups shut down too quickly from a social planner's perspective. OECD (2023) emphasizes the importance of considering this sort of quality effect in digital markets since network effects and ecosystem dominance make it hard to displace low-quality incumbents.

A final contribution of the paper is to document new stylized facts about platform firms and their acquisitions. First, we show that the cross-industry acquisitions we study constitute the majority of platform acquisitions. Second, these acquisitions span a large share of industries: 61% of all industries experienced at least one platform acquisition between 2010-2020. Third, we provide measures of the aggregate importance of platforms based on retail sales, revenues, stock market valuations, and time use surveys.

Related Literature This paper is closely related to two strands of literature in macroeconomics. The first studies the market for firms and its effects on firm dynamics, growth, and welfare (Atalay, Hortaçsu, and Syverson 2014; David 2020; Bhandari and McGrattan 2020; Bhandari, McGrattan, and Martellini 2022; Weiss 2023; Celik, Tian, and Wang 2022; Chatterjee and Eyigungor 2023; Liu 2023; Berger et al. 2023; Fons-Rosen, Roldan-Blanco, and Schmitz 2024).[2] Relatedly Akcigit, Celik, and Greenwood (2016) study the market for patents and Pearce and Wu (2023) study the market for trademarks. Motivated by the recent policy debate on digital markets, we contribute a model with an explicit platform technology and show that platform acquisi-

[2]These papers, and ours, build on insights from earlier research about the various motives for acquisitions ranging from reallocation of capital from low to high productivity firms, complementarities between merging firms, and economies of scale (Jovanovic and Rousseau 2002; Rhodes-Kropf and Robinson 2008; Hoberg and Phillips 2010; Mermelstein, Satterthwaite, and Whinston 2020).

tions have theoretically ambiguous effects on growth through a novel channel: tying.

The second literature we contribute to studies of the emergence and welfare effects of platforms (Rochet and Tirole 2003; Rochet and Tirole 2006; Brynjolfsson, Chen, and Gao 2022; Alvarez et al. 2023; Rachel 2024; Heidhues, Köster, and Kőszegi 2024; Shamsi 2024) and of digital technologies more broadly (Begenau, Farboodi, and Veldkamp 2018; Jones and Tonetti 2020; Beraja, Yang, and Yuchtman 2022; Farboodi and Veldkamp 2023; Dolfen et al. 2023; Baslandze et al. 2023; Cavenaile et al. 2023; Acemoglu et al. 2023; Acemoglu et al. 2024; Greenwood, Ma, and Yorukoglu 2024). Our primary contribution is to provide a novel and tractable model with product tying, a key feature of platforms' strategic behavior, and to use a dynamic general equilibrium model to study the way that tying and acquisitions interact to affect entry.

There is also a body of partial equilibrium studies of mergers and acquisitions (M&A) in digital markets (Kamepalli, Rajan, and Zingales 2020; Bryan and Hovenkamp 2020; Motta and Peitz 2021; Cabral 2021; Eisfeld 2023).[3] We formalize the argument of Cabral (2021) that merger policy may be a blunt tool to address other aspects of competition in digital industries. Kaplow (2021) calls for a multi-sector, dynamic analysis of digital merger policy because acquisitions can create cross-industry distortions. Our contribution is to develop and quantify such a model.[4] We view our work on cross-industry acquisitions as complementary to the growing literature on within-industry acquisitions (Cunningham, Ma, and Ederer 2020; Kamepalli, Rajan, and Zingales 2020; Fons-Rosen, Roldan-Blanco, and Schmitz 2024).

Beyond merger policy, Evans and Schmalensee (2013) summarize antitrust issues, including tying, in platform-based markets. Fumagalli and Motta (2020) and Ide and Montero (2024) study tying in partial equilibrium. Gutiérrez (2023) provides a case study of Amazon's fee structure, focusing on the dynamic choice of fees, and analyzes the welfare effects of separating Amazon's retail and platform businesses. Several papers study competition, interoperability, and fee design among different platforms (Athey and Morton 2022; Lu, Goldfarb, and Mehta 2024; Jeon and Rey 2024; Ekmekci, White, and Wu 2024).

[3]There is also a large empirical literature studying the effects of M&A on markups, innovation, productivity, and competition (Phillips and Zhdanov 2013; Seru 2014; Blonigen and Pierce 2016; Stiebale 2016; Wollmann 2019; Renneboog and Vansteenkiste 2019; Warg 2022; Ederer and Pellegrino 2023; Hoberg and Phillips 2024). See Kokkoris and Valetti (2020) for a summary.

[4]Contemporaneous work by Heidhues, Köster, and Kőszegi (2024) proposes but does not quantify a theory of digital ecosystems.xx

2 Platforms: Recent Trends

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

Cross Industry Acquisitions. The SDC Platinum Database records the universe of M&A deals over $1 million involving U.S. firms from 1990 onwards. Information includes the acquirer name, target name, transaction price, industry classification and some financial information for publicly listed parties. To this dataset we add VentureXpert data on target age and number of employees and use a fuzzy matching procedure to add data on patents from the U.S. Patent and Trademark Office.[5] We focus on GAFAM, motivated by the policy discussion around these particular firms. The sample period is 2010-2020.

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

Platform acquisitions are important from a macroeconomic perspective: the share of U.S. GDP in NAICS4 industries that had at least one GAFAM acquisition between

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

	GAFAM	Top 25 Tech	Top 25 PE	Top 25 S&P
NAICS6, %	83	81	64	61
SIC4, %	74	79	65	60
SDC Tech Class., %	69	59	48	46
B2C Targets, %	26.6	8.4	3.1	3.2
N	467	1114	3790	3498

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

2010 and 2020 is 55%. 61% of all NAICS4 industries experienced at least one acquisition by GAFAM between 2010 and 2020.

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

One measure is e-commerce. Since 2000, e-commerce retail sales have grown at a pace of 16% per year, compared to 4% annual growth of total retail sales. e-commerce now accounts for 16% of all retail sales and continues rapidly expanding. Retail sales in turn account for about 10% of total private final consumption expenditure. Not all e-commerce is done through platforms, so this may overstate the importance of platforms, though Amazon alone controls 40% of the U.S. e-commerce market (Forbes 2024). On the other hand, Big Tech firms do not just sell to final consumers, they also sell their services, such as Microsoft Office or Amazon Web Services, to other firms which is missed in retail sales. The revenue share of GAFAM in total U.S. non-farm, non-financial revenues was 11% in 2021.

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 of these firms as in Boppart et al. (2024), who find that the GAFAM firms are all among the top ten firms expected to contribute the most to future earnings growth. As of July 2024 these five companies had a combined market capitalization of $12 trillion and made up 27% of the S&P500.

A final way to measure the significance of digital platforms is time use. A representative survey from Nielsen's (2021) for the U.S. population shows 3.8 total hours spent online each day between computers and mobile devices. A different 2023 survey found that U.S. users spent 4.2 hours per day on various social media platforms (Emarketer 2023). Restricting attention to online shopping, households spend a little over an hour per week shopping online (SWNS 2024).

3 Baseline Model

The economy consists of a growing mass of products whose consumption by households is intermediated by a platform. An online retail platform like Amazon is a natural example.[6] Some products are produced by the platform itself (e.g. Amazon Basics) and some are sold by third party sellers who we call startups. Households choose how much to use the platform, with greater use improving the shopping experience but incurring a time cost. Potential new startups make a forward-looking entry decision.

3.1 Environment

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

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

Real consumption is aggregated across products $i \in [0, N_t]$, where N_t is the measure of products available at time t, using a constant elasticity of substitution (hereafter, *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 and $\alpha_{i,t}$ is a demand shifter related to the platform that we explain shortly.

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

Labor L_t is devoted to three activities: production of consumption goods $L_{Y,t}$ and starting new businesses $L_{E,t}$, both of which earn labor income, and using the platform $L_{P,t}$, which does not. All three activities trade off with leisure time. The household owns a representative portfolio of firms that pays out the aggregate profits as dividends. The household's budget constraint is thus

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

where a_t is the savings in the form of the representative portfolio, r_t is the interest rate, Π_t is the aggregate profit of firms in the form of a dividend, and $p_{i,t}$ is the price of product i. Throughout the paper, the wage rate is normalized to 1.

Three results follow, which we derive 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: N_{Pt} products are sold by the platform, and N_{St} products are sold by startups. All producers have a constant labor productivity of one and labor is the only input to production.

Product Quality with Platform-Based Consumption. In addition to its role as a producer, the platform firm intermediates consumption. This intermediation process determines quality α_{it} for each good i. Each product has a baseline quality of 1 (e.g. the quality if bought offline). On top of this, the platform 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 technological benefit γ to share with third party sellers, in a decision we call tying. The platform chooses δ_t so that:

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

The endogenous choice of tying represents a wide range of behaviors the platform can engage in to decrease the appeal of third-party products, for example, limiting sellers' access to data and back-end code and reducing interoperability (Kamepalli, Rajan, and Zingales 2020), bundling platform-owned products together (OECD 2023), or reducing the performance of third-party apps on its platform to increase demand for its own apps (Department of Justice 2024). Section 7.1 considers an alternative assumption that the platform charges startups to sell on the platform, creating a market for platform services, and faces a cost to providing these services, relaxing the assumption that sharing the platform's technology is costless. We show a similar strategic incentive arises in this alternative model.

Entry Dynamics. The measure of startups N_{St} grows through the creation of new startups and shrinks when startups are acquired by the platform. There is a large measure of potential entrants who can create new startups using labor. The entry cost is a function of the stock of varieties N_t as in Romer (1990) and increasing in the growth of new varieties (Acemoglu et al. 2018; Klenow and Li 2024). More specifically, at time t, the entry cost is $\frac{\kappa(g_t)}{N_t}$ where

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

After entering the startup's product line stays in operation forever.[7]

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

[7] An extension with endogenous exit and heterogeneous productivity is discussed in Section 7.2.

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 of share of total goods (e.g. having a wide range of products from clothing to electronics to cloud services to video streaming.) Ecosystem dominance grows through acquisitions but shrinks as new startups are founded.

Discussion. Before moving on to the characterization of the equilibrium, we discuss the economic content of the key ingredients of our model. First, we assume that the platform increases the intrinsic quality of the product. We view this as a reduced-form representation of the role of the platform in the consumption process, which could encompass improved service quality or reduced shopping costs. An alternative way to model the platform is through productivity. Regarding theoretical predictions, the productivity model is isomorphic to our model. Second, although our model has only one platform, this single platform does face competition. This competition comes from the substitution of consumption between platform-owned products and standalone products and household substitution in platform usage and leisure.

3.2 Equilibrium

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

Pricing Equilibrium. In our baseline model, we assume that all products (regardless of whether they are a platform firm or a startup) compete in a monopolistically competitive manner. Section 6.1 considers the case where the platform prices its products jointly, leading the platform to charge a variable markup and creating an additional distortion from ecosystem dominance.[8]

[8] The calibrated model in Section 6 also assumes joint pricing. Our main focus is on the growth effects of platform acquisitions rather than static distortions, so we focus on constant markups to keep the analytical results parsimonious.

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

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

by substituting qualities into equation 4.

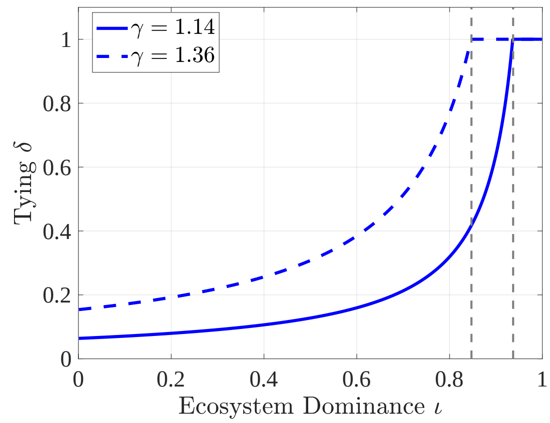
The price index has three components. Two of them, the markup and the love of variety, are standard. The third component is new: the platform's technology, ecosystem dominance, tying, and the household's platform time use all affect the price of real consumption. All else equal the price of real consumption falls when (i) the household uses the platform more frequently ($\frac{\partial P_t}{\partial L_{P,t}} < 0$); (ii) more products are in the platform's ecosystem ($\frac{\partial P_t}{\partial \iota_t} < 0$); (iii) platform does not engage in much tying ($\frac{\partial P_t}{\partial \delta_t} > 0$).

Before explaining the determination of equilibrium $L_{P,t},\ \iota_t,$ and δ_t, it is helpful to write out the firms' profits given these variables. We will focus primarily on a balanced growth path where N_t grows at a constant rate. On this balanced growth path, the earnings of all operating firms decrease exponentially because the number of varieties is growing. We characterize the profits of the firms a time t as $\frac{\pi_{S,t}}{N_t}$ for the startups and $\frac{\pi_{P,t}}{N_t}$ for the platform products. On a balanced growth path, we show $\pi_{S,t}$ and $\pi_{P,t}$ will both be constant. We refer to these objects as the (detrended) profits throughout the paper:

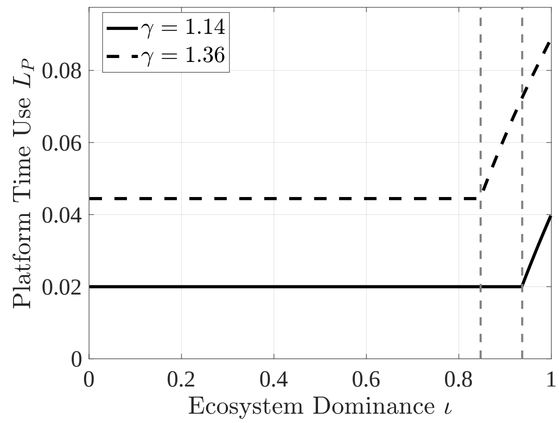
$$\pi_{P,t} = \frac{1}{\sigma} \frac{1 + \gamma L_{P,t}}{1 + \gamma L_{P,t}(\iota_t + (1-\iota_t)(1-\delta_t))}, \tag{7}$$

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

In (7) and (8), $\frac{1}{\sigma}$ is the profit margin since all firms charge a constant markup of $\frac{\sigma}{\sigma-1}$. The platform introduces dispersion of firm profits through their revenues. More precisely, since $\delta_t \in [0,1]$, we can verify that $\pi_{P,t} > \frac{1}{\sigma} > \pi_{S,t}$, where $\frac{1}{\sigma}$ would be the profit for an individual firm in a standard model. Thus, by manipulating the service provided to other firms, the platform gains advantages for all of its products. This strategic incentive introduces novel implications for growth, as we show later.



(a) Tying



(b) Platform Use

Figure 1: Tying and platform use as a function of ecosystem dominance for two different values of the platform technology γ.

Platform Time Use. The household takes tying and prices as given and chooses how much time to spend using the platform.[9] The household faces a trade-off between leisure time and higher real consumption when choosing L_P. The optimal choice equates the marginal benefit and marginal cost of using the platform. The household's problem can be written

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

s.t.

equation (6).

The solution is

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

The key result is that household platform use is decreasing in platform tying δ_t as long as ecosystem dominance is less than one. Before discussing household platform use further we solve for equilibrium tying.

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

Tying. The platform chooses tying δ_t to maximize profits (equation 7) taking into account the effect of tying on household platform use (equation 10).[10] This introduces the key tradeoff: tying increases the relative attractiveness of the platform's own products compared to startups, but reduces household platform use, thereby depressing demand for all goods in the economy, including the platform's. The solution 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 for two different values of γ. Tying is increasing in the platform's ecosystem dominance ι_t and in the platform technology γ until tying reaches one. Even when the platform sells a very small share of products (ecosystem dominance is low) tying is positive because the effect of discouraging usage in equation 10 is zero when $\delta = 0$. At that point, the startups products and the platform products are identical, thus any change in the platform usage will not affect the platform's profits directly. Any lost profit from platform products will be directly compensated by reallocated market shares from competitors. As $\iota_t \to 1$ platform use no longer responds to tying since the platform de facto owns all products; the benefit of tying also shrinks, but at a slower rate compared to the cost. This leads to maximum tying in this limit. It's possible to reach maximal tying for interior values of ecosystem dominance, and maximal tying is reached faster when the platform technology γ is better (the dotted line in 1a).

Substituting the platform's choice of tying into equation 10 yields equilibrium platform time use, plotted in Figure 1b. When tying is less than one, an increase in ecosystem dominance has two competing effects on platform time use that are exactly offsetting: first, holding tying fixed, greater ecosystem dominance would have a 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, 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 platform time use begins to increase in ecosystem dominance. Figure 1b also gives a sense of how we identify γ in the quantification. Conditional on the elasticity of substitution and ecosystem dominance, there is a direct mapping from platform time use to

[10] The assumption that the tying decision is static is without loss of generality given our assumption about Nash bargaining over the merger surplus.

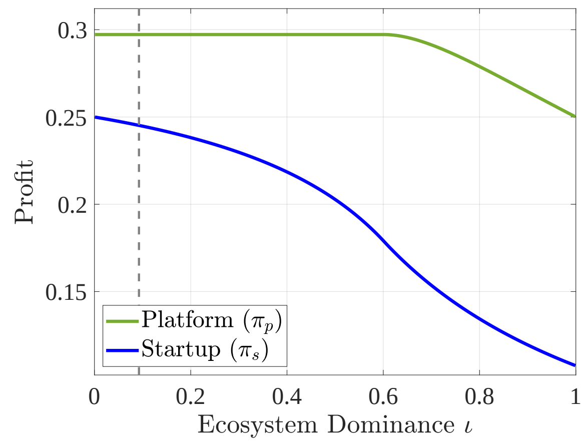


Figure 2: Firm profits as a function of ecosystem dominance in the baseline model.

the platform technology parameter γ: more platform time use suggests the platform technology is better (solid vs. dashed line).

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

Dynamic Equilibrium. The value of a startup determines entry and the value of a platform firm determines the surplus created from acquisitions. We denote the detrended value of a platform firm as v_{Pt} and that of a standalone firm as v_{St}. In other words, the value of these firms at t is $\frac{v_{Pt}}{N_t}$ and $\frac{v_{St}}{N_t}$, where

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

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.2. The platform and startups have the same discount rate. They 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 startups meets the platform for acquisition at rate μ. In these events, the startup receives a share β of the surplus $v_{Pt} - v_{St}$.

Positive entry requires that new startups must be indifferent about whether to enter. In the aggregate with growth rate g_t, the entry cost is $\kappa(g_t)$. Thus, on any equilibrium with positive entry, $\kappa(g_t) = v_{St}$ for any t. Combining this condition 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 yields the value of a platform firm 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.

According to the entry and acquisition dynamics, ecosystem dominance changes according to the following law of motion:

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

Given a fixed growth rate (and thus a fixed entry rate of startups), a higher acquisition rate μ increases the ecosystem dominance of the platform. Given a fixed acquisition rate, a higher startup rate 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.*

More specifically, given the forward-looking value function, we require that the growth rate of this economy must be consistent with firms' values and free-entry, and hence equation (15). Given the growth rate of the economy, we require that the ecosystem dominance follows its dynamics, and hence condition (16).

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

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

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

(labor)

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

Note in equation (17) that total entry costs are $\kappa(g_t) \times g_t$ (the per-firm cost is $\kappa(g_t)$).

3.3 Special Case: Balanced Growth Path

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

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

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

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

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

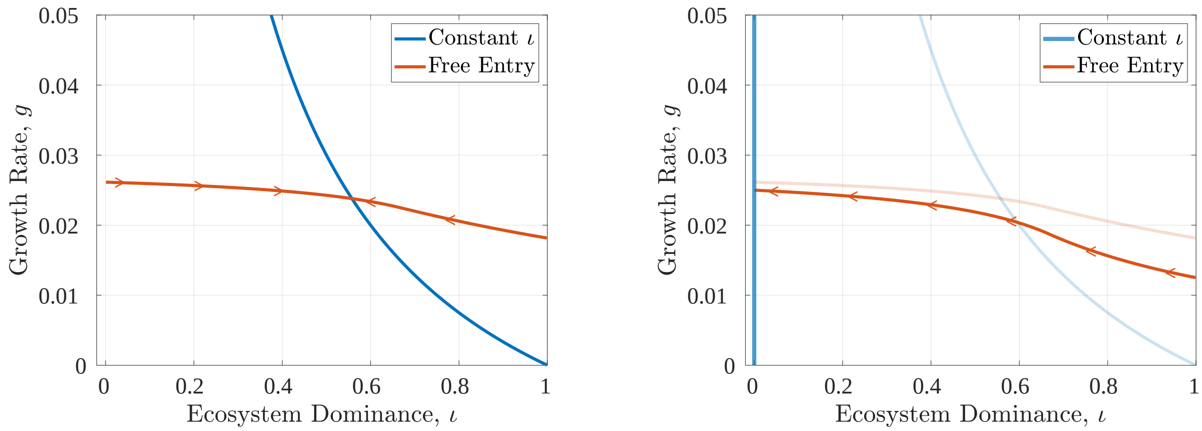
4 Effect of An Acquisition Ban on Growth

Returning to the central question of the paper: what happens to the economy's growth rate if policymakers regulate platform acquisitions more strictly? The answer turns out to be different in the short and long run, so considering the transition between steady states is crucial. We consider the case of a total acquisition ban here, and derive a local result for small changes in the acquisition rate in Appendix B.5.

With one more assumption on the form of entry costs, the model is simple enough to analytically characterize the path of the growth rate over the transition. The assumption needed is that the entry cost is constant: $\kappa(g) = \kappa$, that is, $\eta = 0$.

Suppose the economy is on a balanced growth path with $\mu > 0$. At time 0, the government bans platform acquisitions, setting $\mu = 0$. Given this policy, the platform's ecosystem dominance monotonically decays at rate g_t starting from $\iota(0) = \iota_0^*$. The transition path of ecosystem dominance is $\iota_t = \iota_0^* \exp\left(-\int_0^t g(\tau)d\tau\right)$.

When the option value of acquisition disappears, startups' values come only from their operating profits $\pi_s(\iota_t)$. The growth rate on the transition path thus equates the



(a) BGP with Acquisitions

(b) BGP with No Acquisitions

Figure 3: Impact of Acquisition Ban on BGP

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

entry cost to the operating value, for any t:

$$(\rho + g_t)\,\kappa = \pi_s \left(\iota_0^* \exp\left(- \int_0^t g_\tau d\tau \right) \right). \tag{18}$$

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 ($\mu = 0$): $\frac{dg_t}{dt} > 0$ and $g_0 < g_o^*$, where g_0 is the time 0 growth rate on the transition path and g_o^* is the old BGP growth rate with acquisitions.*

The proof is in Appendix B.3. Lemma 2 says two things. First, the growth rate is increasing over the transition to the new steady state. Second, growth immediately falls 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.

Figure 3 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 (panel 3b). The initial growth rate on the transition path g_0 is the intersection of ι_o^* and the new free entry curve, so below g_o^*. Then the economy moves along the free entry curve with growth increasing from g_0 towards the new steady state, which is the intersection of the new free entry curve and the new constant ecosystem dominance curve (any g is consistent with constant ecosystem dominance when μ is 0 so this line is vertical). Figure 4 plots the time paths of the growth rate and ecosystem dominance. Notice in this example, the acquisition ban has a positive effect on the long run growth rate. Lemma 3 derives a condition for this to be true.

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*

$$\underbrace{\beta\left(\frac{\pi^*_{p,o}}{\kappa(\rho + g^*_o)} - 1\right)}_{\text{M \&A Premium}} < \underbrace{\frac{\pi^*_{s,o}}{\kappa}}_{\text{ROE of Targets}} \times \underbrace{\frac{1}{\mu}\left(\frac{1/\sigma}{\pi^*_{s,o}} - 1\right)}_{\text{Change in Profits}}.$$

The proof is in Appendix B.4. Lemma 3 links the effect of an acquisition ban on the long run growth to several objects, potentially measurable in the data.[11] 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.[12] All else equal, if this premium is low, an acquisition ban is more likely to increase growth, because the negative impact of losing out on this premium will have minimal negative effect on entry.[13] The righthand side is larger when the change in startup profits due to the ban is large, for example because tying was severe in the pre-ban equilibrium.

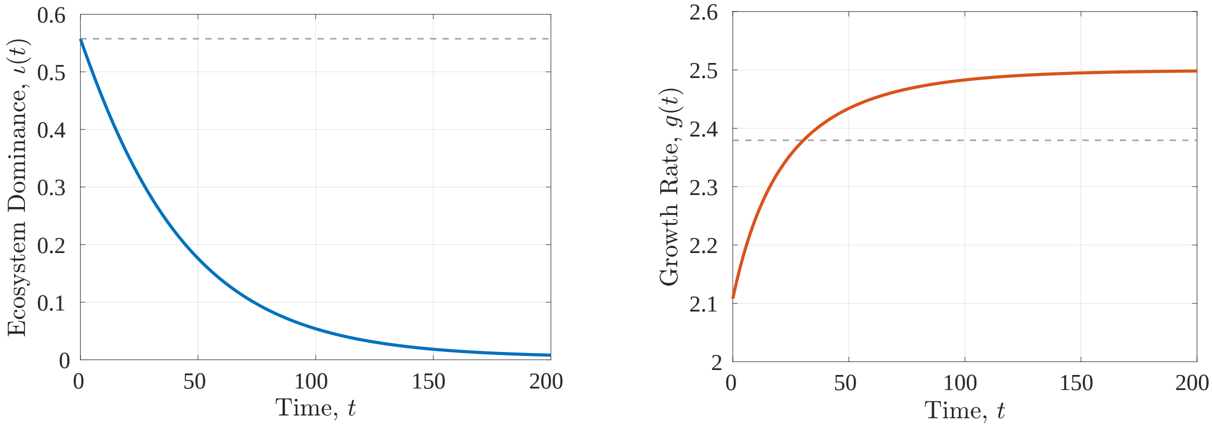
5 Welfare

Turning to normative implications, we first decompose welfare on any balanced growth path into terms that have natural interpretations, then solve for the efficient allocation to highlight distortions. We then return to the impact of an acquisition ban.

[11]The challenge with actually measuring these objects in the data is lack of pre-acquisition valuation and other financial information for target firms, since only six out of the hundreds of targets in our sample were public at the time of acquisition. In the quantification we use indirect inference to estimate the model parameters and check whether this condition holds.

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

[13]Kamepalli, Rajan, and Zingales (2020) argue that startup bargaining power against platforms may be low relative to traditional industries.



(a) Ecosystem Dominance

(b) Growth Rate

Figure 4: Transition Path with Acquisition Ban

Note: The x-axis plots time, and the y-axis plots the ecosystem dominance and growth rate on the transition path towards a BGP without acquisitions. The dashed line indicates the old BGP values of the variables. Both graphs are produced using the same set of parameters as in Figure 3.

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 singles out the role of platform utilization. Given platform time use L_P, tying δ and ecosystem dominance, ι, we define the 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 available and all firms charge their marginal cost of production. This index captures the pure effect of platform use, affected by both the utilization choice of the household and the tying choice of the platform.

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

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

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

The discounted utility of the household on the balanced growth path is

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

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

5.2 Efficient Allocation

Solving for the efficient allocation highlights distortions in the competitive equilibrium and provides a point of comparison for the policy experiments in Section 6. The planner maximizes the discounted utility of the household, subject to the resource constraints:

$$\mathcal{W}^* = \max_{c_{it}, L_t, \dot{N}_t} \int_0^\infty e^{-\rho t} \left[\log C_t - L_t\right] dt, \tag{20}$$

s.t.

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

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

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

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

$$L_P^{SP} = \frac{1}{\sigma - 1} - \frac{1}{\gamma}. \tag{21}$$

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

$$\rho \left(\kappa' \left(g^{SP}\right) g^{SP} + \kappa \left(g^{SP}\right)\right) = \frac{1}{\sigma - 1} + \left(\kappa'' \left(g^{SP}\right) g^{SP} + \kappa' \left(g^{SP}\right)\right) \dot{g}^{SP} \tag{22}$$

Distortions. Markups depress production labor in the standard way, with $L_Y = \frac{\sigma-1}{\sigma} < 1$. Comparing platform time use in equations (12) and (21), it is clear that tying results in under-utilization of the platform by households in the competitive equilibrium.

Tying not only affects the static allocation but also impacts the growth rate. Contrasting the free entry condition (15) to the planner's optimality condition for the growth rate (22) 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.[14] The two 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 of knowledge spillovers to entry costs (the standard lack of appropriability distortion).

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. Whether this policy improves welfare or not depends on the relative importance of the short run and the long run. We again highlight this tradeoff by considering the acquisition ban under constant markups and constant entry costs.

[14]With constant markups as $\beta = 1$ and $\mu \to \infty$ in the decentralized equilibrium, the platform service is also growth-neutral because startups are acquired immediately and capture the full surplus created by the acquisition, equalizing the platform and startup firm values and restoring the pre-platform growth rate.

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

$$\Delta \mathcal{W} = \left(\frac{1}{\sigma - 1} - \rho\kappa\right) \int_0^\infty e^{-\rho t}(g_t - g_o^*)dt. \tag{23}$$

The proof is in Appendix B.7. The intuition is straightforward: with constant markups, there is no change in the markup component due to the ban. Equation 11 shows that declines in ecosystem dominance are exactly offset by declines in tying in how they affect P^u, so the platform component is unchanged. A policymaker can therefore take the decision about whether or not to ban acquisitions in two steps: first evaluate whether the effect of a ban on the long run growth rate is positive. If it is not, the policy is unambiguously bad. If it is, then the policymaker must trade off the short run cost of initially lower growth against the long run benefit of higher growth using the appropriate household discount rate ρ. We always calibrate the model such that the pre-platform growth rate is positive; this requires $\frac{1}{\sigma} > \rho\kappa$. Since $\frac{1}{\sigma-1} > \frac{1}{\sigma}$, the same condition also implies that $\frac{1}{(\sigma-1)} - \rho\kappa > 0$. Thus, an acquisition ban increases welfare if and only if the discounted growth rate in the transition is larger than the discounted growth rate on the old BGP.

6 Quantitative Model

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

6.1 Variable Markups

The platform sets its price p_{Pt} and tying policy δ_t to maximize profits by taking into account their effect on the time spent by the consumer on the platform $L_{P,t}$ and the aggregate price index P_t. The pricing problem is symmetric across all platform products and can be written:

$$
\begin{aligned}
\max_{p_P,\delta} \quad & \pi_P = (p_P - 1)\,\alpha_P \left(\frac{p_P}{P}\right)^{-\sigma} P^{-1} \\
\text{s.t.} \quad & L_P = \left(\frac{1}{\sigma-1} - \frac{1}{\gamma}\frac{\iota p_P^{1-\sigma} + (1-\iota) p_S^{1-\sigma}}{\iota p_P^{1-\sigma} + (1-\iota)\,(1-\delta)\,p_S^{1-\sigma}}\right) \\
\text{and} \quad & P = N^{\frac{1}{1-\sigma}} \left(\iota \alpha_P p_P^{1-\sigma} + (1-\iota)\alpha_S p_S^{1-\sigma}\right)^{\frac{1}{1-\sigma}}, \\
\text{with} \quad & \alpha_i = \begin{cases} 1 + L_P\gamma & \text{platform products (P)} \\ 1 + L_P\,(1-\delta)\,\gamma & \text{startup products (S)} \end{cases}, \quad \delta \in [0,1].
\end{aligned} \tag{24}
$$

Note that P, L_P, α_P and α_S are all functions of p_P and δ. In particular, platform time use L_P decreases in prices. Taking FOCs with respect to p_P and δ:

$$
FOC_{p_P} \quad \frac{1}{p_P}\frac{\sigma - (\sigma-1)s_P}{(\sigma-1)(1-s_P)} + \frac{(p_P - 1)}{(\sigma-1)}\left[\left(\frac{\frac{\partial \alpha_P}{\partial p_P}}{\alpha_P} - \frac{\frac{\partial \alpha_S}{\partial p_S}}{\alpha_S}\right)\right] = 0 \tag{25}
$$

$$
FOC_{\delta} \quad \left[\frac{\frac{\partial \alpha_P}{\partial \delta}}{\alpha_P} - \frac{\frac{\partial \alpha_S}{\partial \delta}}{\alpha_S}\right] + \left[\frac{(\sigma-1)}{p_P}\frac{s_P}{1-s_P}\right] = 0 \tag{26}
$$

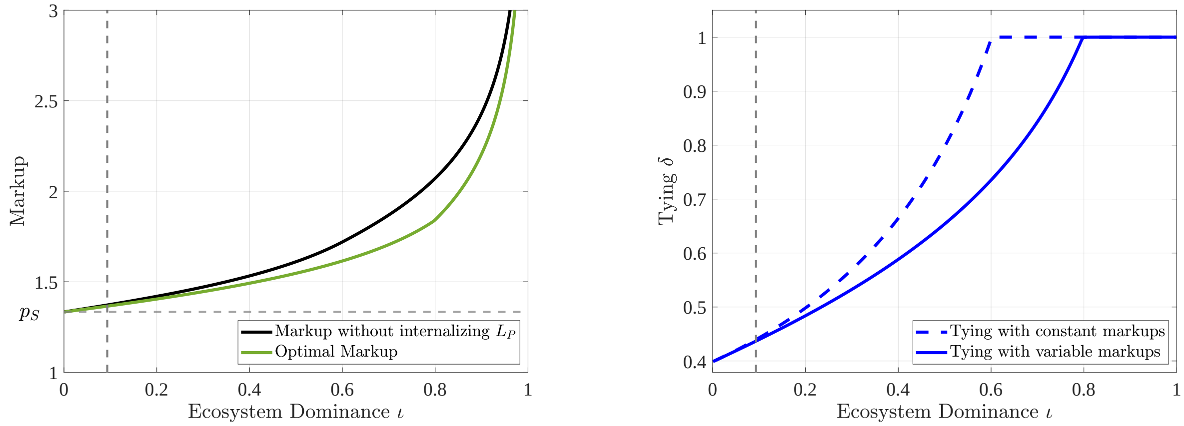
$$
\text{where} \quad s_P \equiv \frac{\iota \alpha_P p_P^{1-\sigma}}{\left(\iota \alpha_P p_P^{1-\sigma} + (1-\iota)\alpha_S p_S^{1-\sigma}\right)} \text{ is the platform's market share.} \tag{27}
$$

The first term in 25 is the one that appears in the standard variable markup case where α_P and α_S are different but constant and a firm with a non-zero mass of varieties imperfectly competes with a competitive fringe of standalone firms. As in the standard problem this term captures the platform's trade-off between its extensive and intensive profit margin when raising the price. The second term captures the marginal effect on the quality spread between the platform and the startups induced by changing time use through prices.

Substituting 26 into 25 yields a simple expressions for the platform's price

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

This is the standard variable markup solution with Bertrand competition, except that the market share $\tilde{s}$ is adjusted downward so that the platform's markup is weakly below the usual markup. This is because platform time use declines in the platform's



(a) Variable markups

(b) Tying with variable markups

Figure 5: Panel (a) compares the standard pricing solution with CES demand and granular market shares (Atkeson and Burstein 2008) to the platform's optimal markup in our model with endogenous platform time use. The dashed line is the startups' markup. Panel (b) compares tying in our baseline model (with constant markups) to the platform's optimal tying with variable markups.

price and in tying, so both $\frac{\partial L_P}{\partial p_P}$ and $\frac{\partial L_P}{\partial \delta}$ are negative, meaning $\tilde{s}_P < s_P$. Figure 5a shows that the adjustment coming from endogenous platform use is small in our calibrated model, especially for low levels of ecosystem dominance. Figure 5b compares tying in the baseline constant markup model to tying with variables markups. When the platform can adjust prices as well as tying, tying is lower for the same level of ecosystem dominance, though for low values of ι this difference is small. As with growth, the positive effects of an acquisition ban on markup dispersion take time to materialize as ecosystem dominance decays over time.

6.2 Calibration

The calibration proceeds in several steps. First, we take standard values for household preferences from the literature, setting $\rho = 0.02$ (for an annual real interest rate of 2%) and $\sigma = 4$ (this implies firm-level markups for startups of 33%, in line with the estimates of De Loecker, Eeckhout, and Unger (2020) and De Ridder, Grassi, and Morzenti (2024)). We set the target's (startup's) bargaining power $\beta = 0.5$ as estimated by David (2020). We explore the sensitivity of the policy conclusions to all of these choices. Finally, we follow Acemoglu et al. (2018) in setting $\eta = 1$.

Second, we compute a "pre-platform" steady state of the model to calibrate the

	Value	Meaning
ρ	0.02	Discount rate (annual)
σ	4	Elas. of substitution
κ	52	Entry cost
η	1	Entry curvature
γ	6.98	Platform technology
μ	0.0061	Merger meeting rate
β	0.5	Entrant barg. power

Table 2: Model parameters, baseline.

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

Third, we compute a new "platform" steady state to calibrate the platform technology parameter γ. Our model measure of time spent on the platform is L_P. We take the data analog of this moment to be time spent online from Nielsen's (2021) by U.S. households. U.S. households spent 3.8 hours per day online across computers, smartphones and tablets in 2021. Given the uncertainty around how much of this time is spent engaging in the sort of activities our model captures, we also explore the sensitivity of our results to this choice.

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

Table 4 demonstrates the model fit for the pre-platform and platform economies. The model is capable of fitting platform time use and the platform's revenue share exactly using the two parameters γ and μ. The parameter choices imply tying of 44%, meaning 56% of the platform's appeal is shared with startups. As a warmup for welfare comparisons, the middle panel reports the steady state welfare gain associated

	Data	Pre-plat.	Plat.
Growth rate, %	2.000	2.003	1.999
Platform time use, hours/day	3.8	0	3.8
Platform revenue share, %	11	0	11
Tying δ, %	-	0	44
Welfare, CE % chg.	-	-	1.5
growth	-	-	-0.2
platform	-	-	11.2
markup	-	-	-0.3
prod. cost	-	-	0.2
entry cost	-	-	0.1
plat. time use	-	-	-9.5
Discounted Welfare, CE % chg.	-	-	1.4

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.

with the introduction of the platform. Households generate significant benefits by using the platform, but this comes at a time cost. These benefits are large enough to outweigh the slight decline in the growth rate and a slight increase in the markup distortion. The bottom panel reports the *discounted* welfare gain from the point of view of the pre-platform equilibrium which is 1.5%.

	Data	Pre-plat.	Plat.
Growth rate, %	2.000	2.003	1.999
Platform time use, hours/day	3.8	0	3.8
Platform revenue share, %	11	0	11
Tying δ, %	-	0	44
Welfare, CE % chg.	-	-	1.5
growth	-	-	-0.2
platform	-	-	1.7
markup	-	-	-0.1
Discounted Welfare, CE % chg.	-	-	1.6

Table 4: 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.

6.3 Policy Experiments

Table 6 summarizes the results of two policy experiments: an acquisition ban and a tying ban.

Acquisition Ban. An acquisition ban (Table 6, column 2) restores the higher growth and lower markups of the pre-platform equilibrium by reducing ecosystem dominance to zero, thereby reducing tying, without changing platform utilization much compared to the unregulated platform equilibrium, but these welfare gains are so small that the discounted welfare effect of such a policy is essentially zero (bottom panel, the consumption equivalent welfare gain is 0.02%).

	Base.	acq. ban	tying ban	first best
Growth rate, %	1.999	2.003	2.010	5.349
Platform time use, hours/day	3.8	3.8	7.6	7.6
Platform revenue share, %	11	0	9	4
Tying δ, %	44	40	0	0
Welfare, CE % chg.	-	0.18	7.79	59.94
growth	-	0.2	0.6	167.5
platform	-	-0.0	16.9	16.9
markup	-	0.3	0.0	0.2
prod. cost	-	-0.2	-0.0	-0.2
entry cost	-	-0.1	-0.2	-115.1
plat. time use	-	0.0	-9.5	-9.5
Discounted Welfare, CE % chg.	-	0.02	6.59	-

Table 5: Features of model steady state with no policy interventions ("Base."), a policy blocking nearly all acquisitions ($\mu \approx 0$), or a policy banning tying ($\delta = 0$), compared to the first best. CE = consumption equivalent. See section 5.1 for more details on welfare components.

	Base.	acq. ban	tying ban	first best
Growth rate, %	1.999	2.003	2.010	5.349
Platform time use, hours/day	3.8	3.8	7.6	7.6
Platform revenue share, %	11	0	9	4
Tying δ, %	44	40	0	0
Welfare, CE % chg.	-	0.18	7.79	63.72
growth	-	0.2	0.4	52.5
platform	-	-0.0	7.4	7.4
markup	-	0.1	0.0	3.8
Discounted Welfare, CE % chg.	-	0.08	7.79	63.54

Table 6: Features of model steady state with no policy interventions ("Base."), a policy blocking nearly all acquisitions ($\mu \approx 0$), or a policy banning tying ($\delta = 0$), compared to the first best. CE = consumption equivalent. See section 5.1 for more details on welfare components.

Tying Ban. By contrast, a tying ban provides potentially large welfare benefits. Section 5.2 showed that banning tying is part of implementing the first best allocation along with correcting markups and lack of appropriability. A tying ban (Table 6 column 3) eliminates differences in profits for the platform and standalone firms, which increases the long run growth rate even more than an acquisition ban. The bulk of the gains are static and come from eliminating platform under-utilization. Using the platform now generates higher quality across all products in the economy equally. Without tying, households devote more time (twice as much) to using the platform and this results in substantially higher utility from consumption each period. The markup gains are smaller than in the acquisition ban case since the platform maintains a non-negligible 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 in search, reduced Amazon's self-preferencing from 30 ranks to 20; not a complete elimination of tying, but demonstrating that this sort of regulation can affect platform behavior.

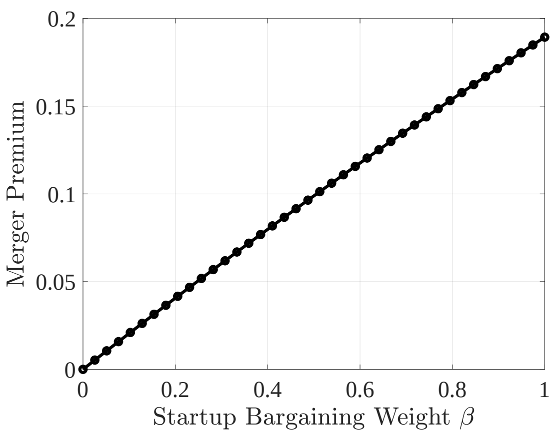
6.4 Sensitivity Analysis

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

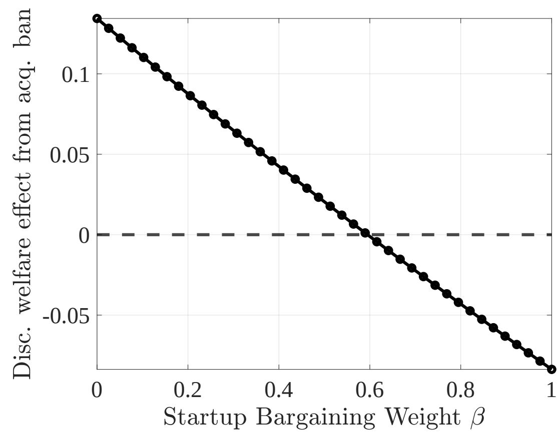
Startup Bargaining Power. We vary the parameter β and compute the competitive equilibrium with all other parameters at their baseline values from Table 2. For each value of β we compute the acquisition premium (defined in Lemma 3) in the competitive equilibrium. Then we compute the discounted welfare change between the competitive equilibrium and an acquisition ban equilibrium under each value of β. The results are plotted in the top panel of Figure 6. Consistent with Lemma 3, the welfare gains from an acquisition ban are larger when the merger premium is low, and turn negative if the premium is sufficiently high, because the policy kills the option value of acquisition which was providing a significant entry motive.

Note that for all possible values of β the acquisition premium in our model is low, at most 20% when startups get the entire surplus, compared to the $\approx 40\%$ number in David (2020), who includes all acquisitions of public firms, and our Table A.1 that focuses on acquisitions of public firms by very large firms. This suggests that we may be understating the costs of an acquisition ban.

Sensitivity of acquisition ban effects to startup bargaining power β.

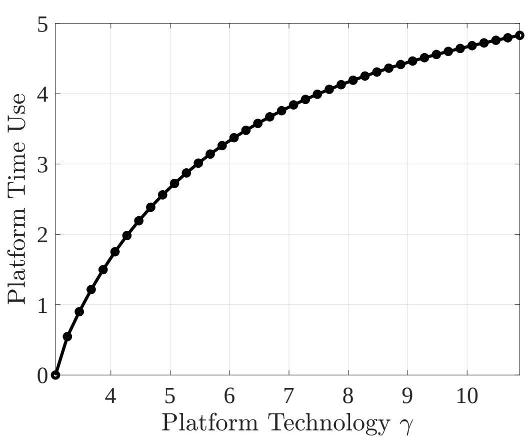


Merger premium.

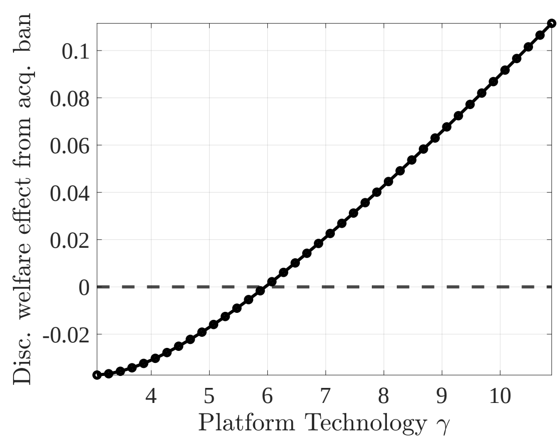


Discounted welfare effect of acquisition ban.

Sensitivity of acquisition ban effects to platform technology parameter γ.



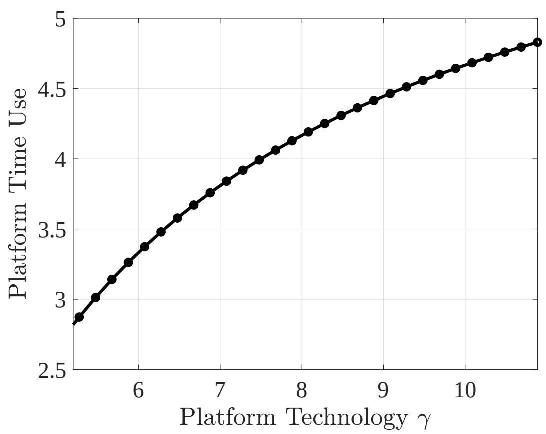
Platform Time Use.



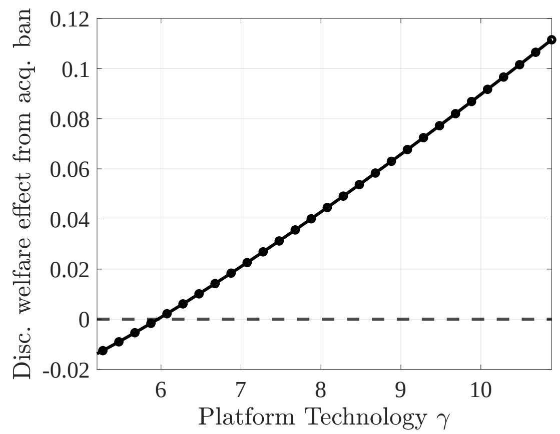
Discounted welfare effect of acquisition ban.

Figure 6: Sensitivity analysis for acquisition ban effects.

OLD.

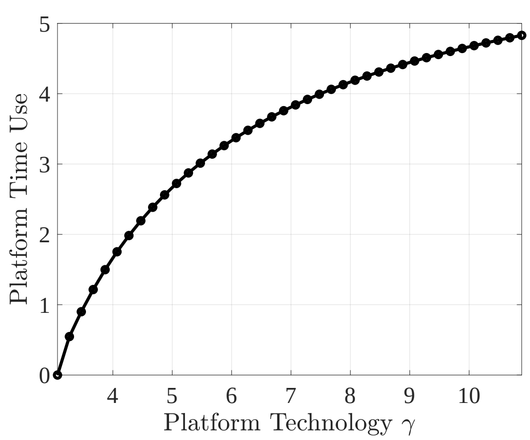


Platform Time Use.

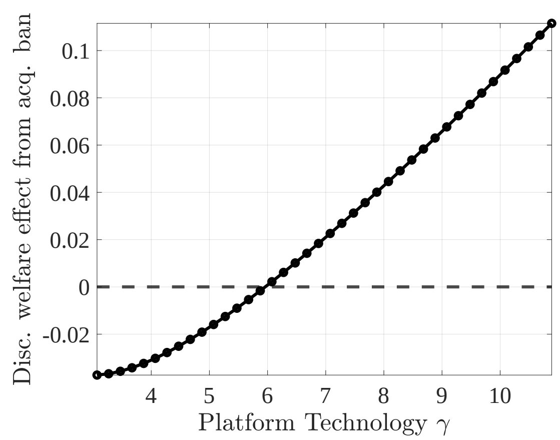


Discounted welfare effect of acquisition ban.

NEW.



Platform Time Use.



Discounted welfare effect of acquisition ban.

Figure 7: Compare Old and New Gamma Sensitivity.

Platform Technology. Since it's not clear how to map the time use survey data exactly to time use in our model, we explore alternative targets for time use L_P that imply different values of the platform technology parameter γ. Varying γ affects the platform's revenue share, so we also re-calibrate μ each time to match the platform revenue share of 11%. The results are in the bottom panel of Figure 6. When γ is low, the welfare effects of an acquisition ban are more likely to be negative.

Preferences. Given the key tradeoff of an acquisition ban between the short and long run, the discount rate used to calculate welfare gains is important, so we consider a range of alternative values for the planner's discount rate (Caplin and Leahy 2004; Cropper et al. 2014). A discount rate that is just xx percentage points higher than our baseline 2% implies welfare losses (Figure C.2). If the planner uses a lower discount rate than the households the discounted welfare gains from the acquisition ban increase. The gains monotonically increase in σ xx why xx Federico investigate if it's because of the markup/markupdispersion by plotting welfare components?.

7 Model Extensions

7.1 Revenue Sharing

This extension considers an alternative assumption regarding the source of tying. Instead of directly choosing tying as in our baseline model, the platform indirectly affects the startups' utilization of the platform by choosing a price to charge for its services. To do this, we assume that the quality of a product is given by

$$\alpha_{it} = 1 + \gamma L_{Pt} u_{it}^{\epsilon},$$

where $\epsilon \in (0, 1)$ is the utilization elasticity. Additionally, we assume the platform's marginal cost of providing a unit of service is ψ. Given the operating profits, the optimal utilization problem for a startup is

$$\max_u \frac{1}{\sigma} \frac{1 + \gamma L_{Pt} u^{\epsilon}}{1 + \gamma L_{Pt} \left(\iota u_{Pt}^{\epsilon} + (1 - \iota) u_{St}^{\epsilon} \right)} - qu.$$

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

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

Given any level of household time use L_P, the platform's optimization problem regarding its service fee q and self-utilization is

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

Choosing the price for its service is equivalent to directly choosing the level of utilization for the startups. We thus write the platform's problem as follows:

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

We are interested in the relative utilization chosen by the platform for its own products and startups' products. This comparison is summarized in the following lemma.

Lemma 5. *Under the platform's optimal choice of utilization:*

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

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 B.8. There are two pieces to the Lemma. First, under the optimal utilization choice, $u_S < u_P$. The optimal choice of revenue sharing is that startups use less of the platform service than the platform itself, leading to lower perceived quality by the households. This result is isomorphic to our baseline model, where the platform directly controls how much service it provides to the startups.

Second, there are two sources of this under-utilization. Simply from being the monopoly, the platform charges a markup on its service, which induces the startups to under-utilize the platform service. In our environment, a second strategic reason for under-utilization is the tying incentives. To see this, note the ratio of standalone utilization and the platform utilization is less than ϵ, the under-utilization predicted by a standard monopoly model. Thus, in our model, the platform charges a markup that is even higher than the standard monopolistic markup, which induces an additional under-utilization. Our baseline model focuses solely on the tying effect and assumes away the monopolistic distortion in platform services.

To further understand the source of such tying incentives, we return to the objective function of the platform. An increase in utilization of a single product has two effects: a direct impact that increases the focal product's revenue and a business stealing effect that decreases the revenue of all other products. Since only a fraction

ϵ of startup profits are appropriated by the platform, an increase in their utilization brings more cost than benefits when compared with the utilization of a platform firm. The lack of perfect rent sharing is crucial for this result. To see this, we note that the under-utilization vanishes as $\epsilon \to 1$.

7.2 Heterogeneous Firms and Exit

This extension introduces idiosyncratic productivity dynamics at the firm level to the baseline model to study exit dynamics and the quality-based theories of harm for platform acquisitions described by OECD (2023). OECD (2023) argues that a platform's ecosystem dominance may make low-quality platform products hard to for entrants to displace. To formalize this intuition, we build on the theoretical framework of Luttmer (2007). The main result is that the platform introduces negative selection.

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

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

Acquisitions. Search is undirected.[15] As before, meetings between startups and the platform occur at rate μ and the startups' share of surplus is β. Acquired products follow the same productivity process as startups.

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

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

[15] 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 using patent citations as a measure of target quality.

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

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

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

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 (equation 28).

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

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

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

Similarly, a startup has the Bellman equation

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

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

Exit Dynamics. All firms have the option to exit the market. In the platform's case this means shutting down an unprofitable product line without shutting down the platform itself. The platform's exit decision is characterized by an exit threshold a_P. The exit threshold should deliver the same value as exiting, which leads to the value-matching condition $v_P(a_P) = 0$. The exit threshold should also be optimally chosen, which leads to the smooth-pasting condition $v_P'(a_P) = 0$. Similar value matching and smooth pasting conditions for the startups deliver the startup exit threshold a_S.

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

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

and

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

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

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

Corollary 1 demonstrates the negative selection: 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 also 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. We defer further discussion of this extension and the proof of Lemma 6 to Appendix B.9.

8 Conclusion

Platforms intermediate a rapidly growing share of total consumption. We have presented a new model to understand how platform-based consumption affects entrants' incentives to create new products when the platform can engage in product tying and acquire third party sellers. Tying can be broadly interpreted as bundling, discouraging interoperability between third party products and the platform, or engaging in self-promotion in search. The effects of stricter merger enforcement on long run growth are ambiguous. Even when there are benefits in the long run, the short run will invariably feature less entry.

We match time use online and the revenue share of platforms in the U.S. to calibrate the model and show that an acquisition ban has essentially no effect on household welfare measured over the transition to a steady state with no ecosystem dominance. Depending on parameters this effect can be mildly positive or negative. The welfare gains to banning tying, instead, are potentially large, suggesting that other types of regulation may be more effective than merger policy in this context.

Our new framework is quite rich. One question for future work is how the creation of the platform technology, γ, interacts with merger policy and antitrust policy that limit tying. Platforms require significant investment to develop and improve, a feature that is missing from the current setup. In reality platforms also create new products. Investments in new products and the platform technology itself may complement each other. Another interesting avenue for future work is how competition *between* platforms already constrains tying, since competing platforms may seek to attract sellers to their platforms by tying less than their competitors.

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A Data Appendix

A.1 Data Sources

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

1. **Industry specific GDP** Bureau of Economic Analysis, Annual Value added by Industry as a Percentage of Gross Domestic Product, Tables TVA110-A for the years 2017 onwards and TVA106-A for the preceding years.
2. **Retail Sales** U.S. Census Bureau, Retail Sales: Retail Trade [MRTSSM44000USS] retrieved from FRED, Federal Reserve Bank of St. Louis.
3. **Final Consumption Expenditure** Organization for Economic Co-operation and Development, Private Final Consumption Expenditure in United States [USAPFCEQDSNAQ], retrieved from FRED.
4. **E-commerce Retail Sales** U.S. Census Bureau, E-Commerce Retail Sales as a Percent of Total Sales [ECOMPCTSA] retrieved from FRED.
5. **GAFAM revenue** Total Revenues (Compustat code: revt) as reported in the companies' annual income statement of 2021.
6. **Total U.S. non-farm, non-financial revenue** Annual flow of funds tables on FRED St. Louis (code: BOGZ1FA106030005A. Definition: Nonfinancial Corporate Business; Revenue from Sales of Goods and Services, Excluding Indirect Sales Taxes (FSIs), Transactions).

A.2 Summary Statistics for Acquisitions

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

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

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

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

A.3 Evidence for Random Search in Heterogeneous Firms Model

One concern is that acquirers, particularly platforms where startups already sell their products, may not meet startups at random. This could significantly change the predictions of the model if platforms tend to acquire and accelerate only high quality startups. To investigate this in the data, we focus on the GAFAM targets with at least one patent prior to acquisition and use patent citations to measure a target firm's quality relative to otherwise similar firms.[16] This gives us 119 platform targets. For each of these targets we build two control groups:

1. Other targets in the SDC Platinum database (yields 204 control firms on average) with the same:
   - NAIC6 industry code
   - Year of first patent (± 5 years).
   - Year of acquisition or later.
2. Other patenting firms in the USPTO PatentsView data (yields 909 control firms on average) with:
   - Cosine similarity $\theta_{ij} > 0.9$ of CPC codes, computed as

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

     - Vector of firm i across CPC codes: $F_i = \{F_{i,CPC_1}, \ldots, F_{i,CPC_{132}}\}$
     - Share of CPC code k $F_{i,CPC_k} = \frac{n_{i,CPC_k}}{n_i}$ with $n_i = \sum_{k=1}^{132} n_{i,CPC_k}$
   - Same year of first patent (± 1 years)

We then compute, for each target firm i:

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

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

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,

[16] 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. However these measures also do not account for intangible intensity or other quality measures of interest.

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 meaing GAFAM firms tend to receive *fewer* citations than comparable firms. However the means are 3.04 and 2.91, respectively, suggesting that there are a few very high quality targets in the GAFAM group. Still we take this overall as evidence in favor of random search by GAFAM in the M&A market and are reassured by the similarities of the findings regardless of the control group (other patenting targets or all patenting firms).

B Model Appendix

B.1 Derivation of Household's Problem

We start with the expenditure minimization problem:

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

s.t.

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

The solution to this problem gives the standard CES demand curve

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

where

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

The following Bellman equation can characterize 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 $H_t'(a) = 1$ for any t and any a. Using this result, we can re-write the Bellman equation as:

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

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

$$\rho = r_t.$$

B.2 Derivation of Firm Values

We derive the detrended firm values in this section. To start, we denote the value of platform firms as V_{Pt} and the value of standalone firms 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 determines the firm values are:

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

and

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

With the chain rule, we can write

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

and

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

Substituting the time derivatives, we have

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

and

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

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

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

and

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

B.3 Proof of Lemma 2

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

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

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

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

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

B.4 Proof of Lemma 3

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

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

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

B.5 Effect of Local Changes in Acquisition Rate

Section 4 considered a complete ban on acquisitions. Here we derive the analog to Lemma 3 for smaller changes in the acquisition rate, i.e. blocking a higher fraction of deals but still allowing some acquisitions to take place.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

B.6 Planner's Solution

We characterize the solution to

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

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

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

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

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

Differentiating both sides w.r.t. time:

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

Differentiating the Bellman equation, we have

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

From the first order condition:

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

From the differentiated first-order condition:

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

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

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

B.7 Proof of Lemma 4

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

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

We isolate the first component and simplify it:

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

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.8 Proof of Lemma 5

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

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

and

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

Taking the ratio and canceling redundant terms:

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

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

B.9 Heterogeneous Firms Extension

In discussion of the dynamic equilibrium, we focus on a balanced growth path where aggregate productivity A_tN_t grows at a constant rate. Growth in a balanced growth path for this economy comes from creating new products net of exit. To characterize the entry-exit decisions of firms on a balanced growth path with a growth rate of g, we characterize the value of product lines, depending on whether they are owned by a startup or by the platform.

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

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

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

and

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

C Quantitative Appendix

C.1 Sensitivity Analysis for Preference Parameters

These figures show the effect of the preference parameters on the (discounted) welfare effects of an acquisition ban. Formally, we first consider the same path of growth rates and markups as in the baseline acquisition ban case, but discount household welfare (equation 1) using an arbitrary social discount rate $\tilde{\rho}$ in Figure C.2.

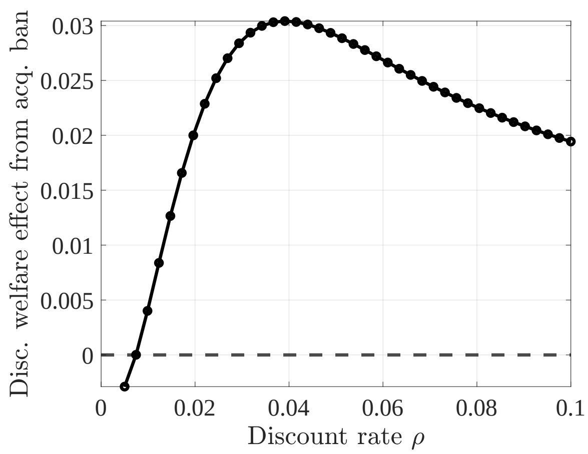
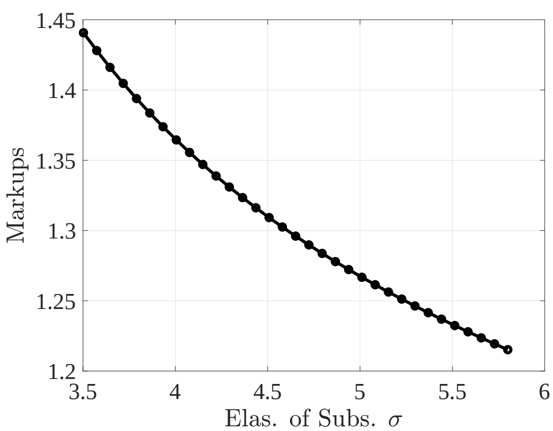


Figure C.2: Sensitivity of acquisition ban effects on discounted welfare to discount factor ρ.

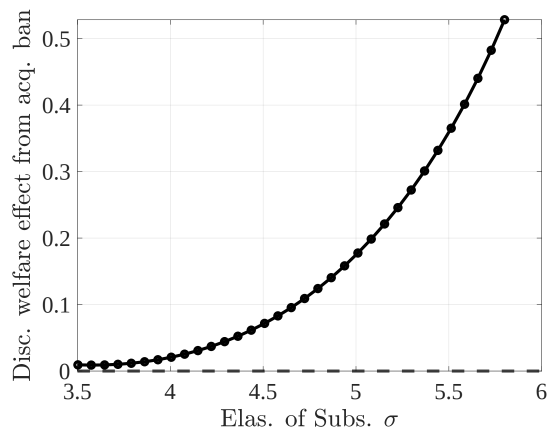
Second, we explore the role of the elasticity of substitution in shaping the welfare effects of an acquisition ban. For each value of σ in the Figure, corresponding to a different startup markup (panel C.3a), we re-calibrate and re-solve the model by:

1. Recalibrating the platform technology γ to match household time use of 3.8 hours/day conditional on the chosen σ.
2. Recalibrating the entry cost κ to match a 2% growth rate in the pre-platform equilibrium conditional on the chosen σ.
3. Recalibrating the acquisition rate μ to match the platform's 11% revenue share in the competitive equilibrium with platform conditional on the chosen σ.

The maximum value of σ in the Figure is the maximal σ consistent with the time use moment we observe in the data. As σ grows a higher and higher γ is needed to match the platform time use moment (equation 12). Eventually there is no value of γ consistent with the time use moment, so this governs the maximal elasticity of substitution we consider.



(a) Platform Markup.



(b) Welfare effects of acquisition ban.

Figure C.3: Sensitivity of markups and acquisition ban effects on discounted welfare to σ.