Platform Acquisitions, Tying, and Growth*

Jane Olmstead-Rumsey Federico Puglisi Liangjie Wu

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Abstract

To understand competition in digital industries we develop a model of consumption through a platform. The platform supplies some of the products in the economy and the rest are supplied by standalone firms. The platform chooses how much of its appeal to share with the standalone firms (''product tying"), balancing the incentive to increase sales of its own products against the desire to attract users to the platform. Acquisitions of standalone firms allow the platform to expand its product offerings and reduce the cost of tying. We use the model to study the effects of acquisitions and product tying on firm entry, household platform use, growth, and welfare. The platform has an ambiguous effect on entry: the option value of acquisition encourages entry while tying discourages it by the reducing the profits of standalone firms. The latter effect dominates quantitatively. In the data, most acquisitions by platform-based "Big Tech" firms are cross-industry and households allocate a significant amount of time to using online platforms.

*Olmstead-Rumsey: LSE (j.olmstead-rumsey@lse.ac.uk). Puglisi: Bank of Italy (federicopuglisi2022@u.northwestern.edu). Wu: EIEF (liangjiewu.robin@gmail.com). We thank Alireza Aarabi and Entian Zhang for excellent research assistance. We thank Jan Eeckhout, Tom Schmitz, John van Reenen and Jinglun Yao for helpful comments and discussions.

1 Introduction

Policymakers around the world are increasingly focused on competition, growth, and mergers in digital markets. Policy proposals in the US, UK, and Europe have singled out the "GAFAM" (Google, Amazon, Facebook, Apple, and Microsoft) group for additional scrutiny 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.

The model features two activities by platforms that regulators are concerned about: acquisitions of other firms, and product tying, a term we use to encompass a broad range of behaviors platforms can engage in that tilt consumption toward platform-owned goods 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 for individual users). Households take as given the total number and quality of products available on the platform, as well as the share and quality of products owned by the platform itself, 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 altogether which depresses aggregate demand, lowering sales and profits.

The dynamic block of the model builds on Hopenhayn (1992), Hopenhayn and Rogerson (1993) and most closely Luttmer (2007). Goods are differentiated and growth comes from the creation of new products by entrants. Idiosyncratic productivity evolves stochastically and, combined with fixed operating costs, generates endogenous shutdown of unprofitable products. In the case of third party sellers, who are

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

single product firms, this entails firm exit. The platform, who owns multiple product lines with different productivities, simply closes down unprofitable lines.

The platform adds new goods to its product portfolio by acquiring small firms. When the platform engages in product tying, such meetings always generate a surplus and both parties would like to merge. The model captures the "ecosystem dominance" theory of harm that acquisitions make it less costly for platforms to engage in product tying, since households have greater incentive to use the platform when the platform owns a larger share of the products in the economy.

Our framework allows us to study how the presence of the platform affects entry, growth, and welfare. We find ambiguous effects of the platform on entry. 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, new to our paper, product tying reduces the standalone value of new entrants and discourages entry.

We also show that the platform induces negative selection. Product tying raises the profits the platform gets from low productivity products and makes them less likely to be shut down. This happens not due to the platform charging higher markups, but simply by the platform selling more of a given good than a standalone firm because of tying. For standalone firms the opposite occurs: tying increases the exit threshold for third party sellers by lowering profits, meaning that some product lines get 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.

Banning tying is the optimal policy and neutralizes the effects of acquisitions. A tying ban increases the steady state growth rate by 5% (0.1 percentage points) while reducing inefficient churn from the premature exit of small firms. It also has a level effect on consumption: banning tying causes households to increase their platform use to the socially optimal level, generating additional network benefits across all goods. Fully eliminating product tying may be difficult in practice so we also consider a policy to block platform acquisitions. Lowering the platform's share of products modestly reduces product tying and has a positive effect on firm entry and growth, suggesting that the negative effect of tying on startup entry dominates the positive option value of acquisition effect in the baseline economy. The welfare gains from the acquisition policy are much smaller than the gains from eliminating tying.

Empirically, we use the SDC Platinum database on mergers and acquisitions to document that cross-industry acquisitions constitute the majority of deals done by the Big Tech firms over the past 15 years and that these acquisitions span a large share of industries. 61% of all NAICS4 industries covering 55% of GDP had at least one GAFAM acquisition between 2010-2020. 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).

Contribution and Related Literature This paper is most closely related to two strands of literature in macroeconomics. The first studies mergers and their effects on firm dynamics, growth, and welfare (Atalay, Hortaçsu, and Syverson 2014; David 2020; Bhandari and McGrattan 2020; Bhandari, McGrattan, and Martellini 2022; Celik, Tian, and Wang 2022; Chatterjee and Eyigungor 2023; Liu 2023; Fons-Rosen, Roldan-Blanco, and Schmitz 2024).[2] Relatedly Akcigit, Celik, and Greenwood (2016) study the market for patents rather than firms, and Pearce and Wu (2023) study the market for trademarks. To this literature, motivated by the recent policy debate on digital markets, we contribute a model that includes an explicit platform-based technology and show that platform mergers generate potentially different effects on firm entry and thus growth and welfare.

The second literature we contribute to studies the emergence and welfare effects of platforms and digital technologies (Farboodi and Veldkamp 2023; Alvarez et al. 2023; Baslandze et al. 2023; Cavenaile et al. 2023; Greenwood, Ma, and Yorukoglu 2024; Rachel 2024) building on the seminal work of (Rochet and Tirole 2003; Rochet and Tirole 2006). Our primary contribution to this literature is to provide a novel and tractable model with product tying, a key strategic feature of platform behavior, and to use a dynamic general equilibrium model to study tying's interaction with acquisitions.

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

[2] These papers, and ours, build on insights from earlier research about the various motives for mergers 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).

partial equilibrium studies of M&A by large firms, with an emphasis on digital markets (Motta and Peitz 2021; Bryan and Hovenkamp 2020; Cabral 2021; Warg 2022). Kaplow (2021) argues that a multi-sector, general equilibrium analysis is needed because of cross-industry distortions.

Evans and Schmalensee (2013) summarize a broader set of antitrust issues, including tying, in platform-based markets. Fumagalli and Motta (2020) study tying in partial equilibrium. Brynjolfsson, Chen, and Gao (2022) estimate the welfare gains from the "long tail" of goods available on a platform.

2 Platforms: Recent Trends

We first use data from SDC Platinum to document that Big Tech firms have recently acquired targets in a large and diverse set of industries. Then, 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 Our primary dataset is the SDC Platinum Database. It records the universe of M&A deals over $1 million involving U.S. firms from 1990 onwards. Information in the dataset includes the acquirer name, target name, transaction price, industry classification and some financial information for both 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. In Table 5, Appendix B, we provide summary statistics about the acquisitions of Big Tech firms and contrast them with deal and target characteristics for other large acquirers. We find that Big Tech firms 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.

In recent years the five largest Big Tech firms have undergone a substantial cross-sectoral expansion, mainly driven by M&A activity, integrating more and more products into their respective platforms. 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.

	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
N	467	1114	3790	3498

Table 1: Source: SDC Platinum. Percent of acquisitions where acquirer (and acquirer ultimate parent) and target have different primary industry codes. "GAFAM": Google, Apple, Facebook, Amazon, and Microsoft. The three other groups are constructed following Jin, Leccese, and Wagman (2022): 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").

In fact most acquisitions by GAFAM are cross industry, regardless of the specific way we define an industry (Table 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 firms acquired by GAFAM operated a platform or other competing service (Argentesi et al. 2020; Parker, Petropoulos, and Alstyne 2021; Jin, Leccese, and Wagman 2022; Jin, Leccese, and Wagman 2023) .

To assess how important these acquisitions are from a macro perspective, we compute the share of U.S. GDP covered by industries that had at least one GAFAM acquisition between 2010 and 2020. 55% of GDP and 25% of employment is in NAICS4 industries where GAFAM did at least one deal over this period. 61% of all NAICS4 industries experienced at least one acquisition by GAFAM between 2010 and 2020.

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 activity and discuss the limitations of each.

One possible 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 expand-ing.[3] Retail sales in turn account for about 10% of total private final consumption expenditure.[4] 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.[5] Moreover, Big Tech firms do not just sell to final consumers ("B2C") they also sell their services, such as Microsoft Office or Amazon Web Services, to other firms ("B2B") which is missed in retail sales. To address this, we take total revenue of GAFAM in Compustat in 2021 and divide it by total U.S. non-farm, non-financial revenues from the BEA, which results in a revenue share of 11% for these five companies.

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 make up 27% of the S&P500.

A final way to measure the significance of digital platforms is time use data. 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. Allocating this time to individual platforms is not possible in the Nielsen data. A different 2023 survey found that U.S. users spent 4.2 hours per day on various social media platforms.[6] This substantial amount of daily engagement highlights the centrality of platform-based firms in the daily lives of consumers and underscores their significant influence on user behavior and digital consumption patterns.

3 Model

Time is continuous. There is a representative household that supplies $L(t)$ units of labor and derives utility from real consumption $C(t)$. The discounted utility of this

[3] U.S. Census Bureau, E-Commerce Retail Sales as a Percent of Total Sales [ECOMPCTSA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/ECOMPCTSA, July 2, 2024.

[4] U.S. Census Bureau, Retail Sales: Retail Trade [MRTSSM44000USS] over Organization for Economic Co-operation and Development, Private Final Consumption Expenditure in United States [USAPFCEQDSNAQ], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/USAPFCEQDSNAQ, July 2, 2024.

[5] Forbes (2024).

[6] https://www.emarketer.com/chart/263759/average-time-spent-per-day-by-us-adult-users-on-select-social-media-platforms-2023-minutes

representative household is given by:

$$\int_0^\infty e^{-\rho t} \left[\log C(t) - L(t)\right] dt.$$

Real consumption is aggregated across a continuum of imperfectly substitutable products. At each instant t, there are $N(t)$ of these products, with an index $i \in [0, N(t)]$ through a constant elasticity of substitution (hereafter, *CES*) aggregator. Specifically,

$$C(t) = \left[\int_0^{N(t)} \phi_i(t)^{\frac{1}{\sigma}} c_i\left(t\right)^{\frac{\sigma-1}{\sigma}} di\right]^{\frac{\sigma}{\sigma-1}},$$

where $\sigma > 1$ is the elasticity of substitution across products. This CES demand system is otherwise identical to the ones in the literature, except for an explicit model of platform usage through appeal of product i, $\phi_i(t)$. This appeal depends on whether product i belongs to the platform:

$$\phi_i\left(t\right) = \begin{cases} 1 + \Phi(t)\Delta & \text{platform owned goods (P)} \\ 1 + \Phi(t)\left(\Delta - \delta(t)\right) & \text{standalone firms (S)} \end{cases}.$$

All products provide a baseline appeal of 1, and additional appeal through the service provided by the platform. The platform leads to an additional appeal of Δ. Δ is a technological parameter of our model (for example, reduced search costs or ease of use). How much a product benefits from the technology advantage of the platform depends on the aggregate platform usage $\Phi(t)$, which is a decision from the household. As the household uses the platform more intensively ($\Phi(t)$ increases), every product provides a higher appeal, capturing network effects.

While goods produced by the platform-owned firms receive the full gains of platform service, $\Phi(t)\Delta$, goods produced by standalone firms, who we refer to as startups, enjoy only some of the benefits of the platform. We introduce a tying choice of $\delta(t)$. The platform can offer only part of its service to the standalone firms by setting a larger $\delta(t) \in [0, \Delta]$, which reduces the gains for the standalone firms. 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 (Kamepalli, Rajan, and Zingales 2020), bundling platform-owned products together (OECD 2023), or, as recently alleged by the U.S. Department of Justice against Apple, reducing the performance of third-party apps on its platform to increase demand for its own apps.[7]

[7] "Justice Department Sues Apple for Monopolizing Smartphone Markets," 21 March 2024. https://www.justice.gov/opa/pr/justice-department-sues-apple-monopolizing-smartphone-markets

Firms. Startups are single-product firms, and the platform owns some mass of products $N_{P,t}$. The number of products N_t is an endogenous variable that is affected by firm entry and exit decisions. There is a large measure of potential entrants who can create a new startup by paying a labor cost of $\frac{\kappa}{N_t \bar{Z}_t}$ where Z_t denotes the average productivity of all goods at time t. To generate exit dynamics, we assume operating a product line incurs an operating cost of $\frac{\psi}{N_t \bar{Z}_t}$, and productivity is stochastic. New entrants start with labor productivity of 1, and productivity then fluctuates according to a geometric Brownian motion with volatility ν. We denote the log productivity of product i at time t as $z_i(t)$. Each platform product requires the same operating cost $\frac{\psi}{N_t \bar{Z}_t}$ as the startups and follows the same stochastic productivity process.

Mergers. The platform and startups can occasionally meet and decide whether to merge. These merger events happen with rate μ.[8] The two parties then decide on whether to merge. If they merge, the startup claims β share of the joint surplus while the platform claims $1 - \beta$ share.

3.1 Static Equilibrium

Pricing Equilibrium. We start by characterizing the pricing equilibrium among firms, conditional on the aggregate platform usage $\Phi(t)$ and the productivity density function of all products in the economy, denoted by $f(z,t)$. The assumption that all products are infinitesimal and the aggregator is CES imply that, in the pricing equilibrium, all products are priced at a constant markup over their marginal costs: $p_i(t) = \frac{\sigma}{\sigma-1} e^{z_i(t)/(1-\sigma)}$.

We define the aggregate price index as $P(t) = \left[\int_0^{N(t} p_i(t)^{1-\sigma} di\right]^{\frac{1}{1-\sigma}}$. Using the equilibrium prices, we derive the aggregate price index of this economy

$$P_t = \underbrace{\frac{\sigma}{\sigma - 1}}_{\text{Markup}} \times \underbrace{(\bar{Z}_t N_t)^{\frac{1}{1-\sigma}}}_{\text{Agg. Quality}} \times \underbrace{(1 + \Phi_t \Delta - \Phi_t \delta_t (1 - \iota_{P,t}))^{\frac{1}{1-\sigma}}}_{\text{Agg. Platform Complementarity}}.$$

The aggregate price index can be decomposed into three components. Relative to models in the literature, our model introduces the endogenous platform complementarity. In addition to the exogenous gains from platform service, Δ, the aggregate

[8] In Appendix B.2, 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.

complementarity also depends on the usage $\Phi(t)$, the tying choice $\delta(t)$, and the *ecosystem dominance* of the platform $\iota_P(t) = \frac{N_{P,t}}{N_t}\frac{\bar{Z}_{P,t}}{\bar{Z}_t}$. Ecosystem dominance measures the relative productivity of platform-owned goods to the entire economy. The dominance comes either from supplying a large share of all products ($N_P(t)$ is higher) or from having higher average productivity ($\bar{Z}_P(t)$ is higher). When $\iota_P \to 1$, either because the platform owns all the products or the platform products are infinitely better than the startup products, tying does not matter for the aggregate price, and vice versa.

Using these notations, we now write out the profits for startups and the per-line profits of the platform. We will mostly focus on a balanced growth path, where $N_t\bar{Z}_t$ grows at a constant rate. For expositional convenience, we define a detrended profit for startups $\pi_{S,t}$ and for platforms, $\pi_{P,t}$. These profits are:

$$\pi_{P,t} = \frac{1}{\sigma}\frac{1+\Phi_t\Delta}{1+\Phi_t\Delta - \Phi_t\delta_t(1-\iota_{P,t})},$$

and

$$\pi_{S,t} = \frac{1}{\sigma}\frac{1+\Phi_t(\Delta-\delta_t)}{1+\Phi_t\Delta - \Phi_t\delta_t(1-\iota_{P,t})}.$$

Platform use and tying decisions Households choose how much to use the platform to maximize period utility:

$$\max_{\Phi_t} \log(C_t) - \Phi_t, = \max_{\Phi_t} -\log(P_t) - \Phi_t,$$

where the equality uses the fact that the households preferences imply $P_tC_t = 1$ for all t.

Plugging in the price index yields the following solution that depends on the platform's choice of δ_t:

$$\Phi_t^*(\delta_t) = \frac{\Delta - \delta_t(1-\iota_{P,t}) - (\sigma-1)}{(\sigma-1)(\Delta - \delta_t(1-\iota_{P,t}))}$$

.

Understanding this, the platform chooses its tying parameter δ_t^* to maximize static profits:

$$\max_{\delta\in[0,\Delta]} \pi_{P,t} = \frac{1+\Phi_t^*(\delta)\Delta}{1+\Phi_t^*(\delta)\Delta - \Phi_t^*(\delta)\delta(1-\iota_{P,t})}.$$

Resulting in the solution:

$$\delta_t^* = \frac{\Delta(\Delta-(\sigma-1))}{\Delta+(\sigma-1)}\frac{1}{(1-\iota_{P,t})}.$$

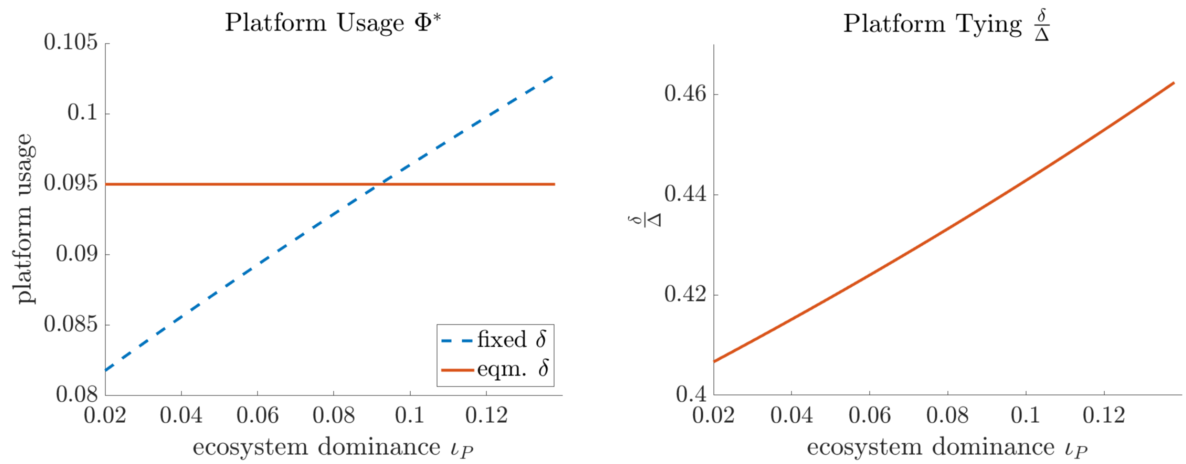

Figure 1: Household platform use and platform tying as a function of platform ecosystem dominance ι_P. Orange lines show equilibrium values and blue line shows counterfactual where tying is fixed at its baseline value and ecosystem dominance varies exogenously.

Tying is increasing in the technological benefit of the platform Δ and in the platform's ecosystem dominance $\iota_{P,t}$. It is decreasing in the elasticity of substitution σ.

Solving for the equilibrium platform use as a function of the platform's optimal tying choice yields an expression for platform use that is independent of ecosystem dominance,[9]

$$\Phi^* = \frac{1}{2}\left(\frac{1}{(\sigma-1)} - \frac{1}{\Delta}\right).$$

Figure 1 illustrates the mechanism for this using the calibrated model from Section 4: any increase in the platform's ecosystem dominance either from acquisition of a new product or relative productivity improvements is exactly offset by an increase in tying so that household platform usage is unchanged and is only a function of the exogenous technology parameter Δ and the elasticity of substitution across goods. Household platform use is decreasing in the elasticity of substitution across goods because generating network effects is less important when goods are more substitutable.

3.2 Value of Firms, Entry, and Exit

In discussion of the dynamic equilibrium, we will focus on a balanced growth path (hereafter, *BGP*). Growth in this economy comes from creating new products (entry

[9] Here we assume $\delta_t^* < \Delta$.

net of exit). To characterize the entry-exit decisions of firms on a balanced growth path with a growth rate of g, we start by characterizing the value of products, depending on whether they are owned by a startup or by the platform.

We denote the value of a startup (which is a single product firm) relative to the entry cost as $v_S(z)$ and the value of a single platform-owned product as $v_P(z)$, both as functions of productivity z. Conditional on operating, the platform-owned product's value evolves according to the following Bellman equation:

$$(\rho + g)v_P(z) = e^z \pi_P - \psi + \frac{\nu^2}{2} v_P''(z). \tag{1}$$

The flow payoff of an operating platform-owned firm is proportional to its productivity z, where the proportion is the per-unit profit π_P. The value function in equation (1) also reflects that the productivity of the product can change over time from the Brownian motion. The focal firm also has the option to exit the market. The exit decision is characterized by an exit threshold z_P. When the firm's productivity is above the exit threshold, it continues to operate; when its productivity falls below the exit threshold, the product line gets shut down. The exit threshold should deliver the same value as exiting, which leads to the value-matching condition $v_P(z_P) = 0$. The exit threshold should also be optimally chosen, which leads to the smooth-pasting condition $v_P'(z_P) = 0$.

Similarly, a startup has the Bellman equation

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

where the startups additionally have a flow benefit from the option value of acquisition by the platform which is increasing in the meeting rate μ and the entrant bargaining power β. Similar value matching and smooth pasting conditions deliver an exit threshold of z_S.

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 (1) and (2). We provide the details of these solutions in Lemma 4 in the Appendix. In the following discussion, we focus on the comparison of exit thresholds.

Lemma 1 (Exit Threshold) *On a balanced growth path, the exit thresholds are solutions to the following equations*

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

and

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

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 (Platform and Selection) *On a balanced growth path,* $z_S > z_P$*.*

Corollary 1 demonstrates the negative selection introduced by the platform: the platform will keep lower productivity product lines active compared to startups. This is the first qualitative result from our model: the strategic tying of the platform leads to more exit of startup firms. A startup faces the tying of the platform and thus suffers a profit loss compared to the platform-owned firms. To justify continuing to operate, startups must have higher productivity. This mechanism leads to two consequences. First, more startups exit the market; Secondly, conditional on surviving, the startups also tend to have a higher productivity than the platform-owned firms.

For most of our quantitative analysis, we will focus on cases with positive growth. The entering firms must break even. Thus the value of an entering firm $v_S(0)$ must equal the entry cost κ. This gives our first equation for the BGP combination of growth rate g and ι_P, the free entry curve:

$$\kappa = \underbrace{\pi_E \frac{1-e^{\eta_E z_E}}{g+\rho+\mu\beta-\frac{\nu^2}{2}}}_{\text{Stand-Alone Value}} + \underbrace{\left(v_P(0) - e^{\eta_E z_E}v_P(z_E) - \frac{(1-e^{(\eta_E+1)z_E})\pi_P}{g+\rho+\mu\beta-\frac{\nu^2}{2}}\right)}_{\text{Option Value of Acquisition}} \tag{3}$$

3.3 Ecosystem Dominance on a BGP

A balanced growth path for this economy is characterized by a growth rate g and a steady state platform ecosystem dominance ι_P which are consistent with free entry and with the shutdown thresholds of firms. These thresholds, combined with the stochastic process for individual productivity, determine the equilibrium productivity distribution across products.

Our second equation for the BGP comes from the productivity distribution of firms. To calculate steady state ecosystem dominance ι_P, we need to characterize two distributions. The overall distribution of firm productivity $f(z)$ and the conditional productivity distribution of startups $f_S(z)$. We also need to know fraction of products $\frac{N_P}{N}$ owned by the platform. We will start by summarizing the final equation for the ecosystem dominance, ι_P, and then expand on the steps to characterize this equation.

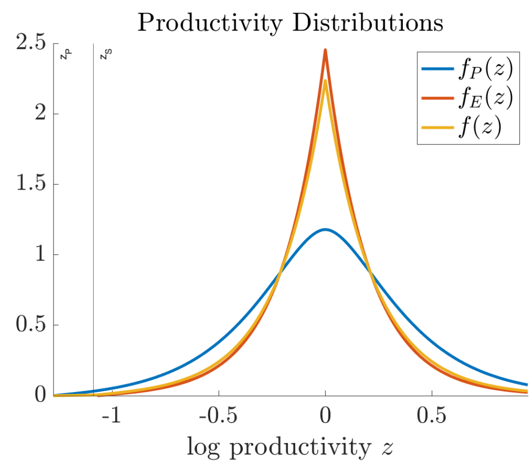

Figure 2: Density on a BGP in the calibrated model in Section 4.

Lemma 2 (Ecosystem Dominance) *On a balanced growth path, the platform's ecosystem dominance is given by*

$$\iota_P = \frac{N_P}{N}\frac{\bar{Z}_P}{\bar{Z}} = 1 - \frac{\left(\zeta_P^2 - 1\right)}{\left(\zeta_S^2 - 1\right)} \frac{\left(e^{(\zeta_S+1)z_S} - 1\right)}{\left(e^{(\zeta_S+1)z_S} + e^{(\zeta_P+1)z_P} - e^{(\zeta_S-\zeta_P)z_S+(\zeta_P+1)z_P} - 1\right)}. \tag{4}$$

To reach this characterization of ecosystem dominance, we separately characterize the density of productivity for startups, the density of productivity for platform-owned firms, and the relative counts of startups and platform-owned firms.

We start with the productivity distribution for startups. This distribution follows a Fokker-Planck equation (KFE):

$$0 = \frac{\nu^2}{2} f_S''(z) - (g + \mu) f_S(z), \tag{5}$$

for almost all points except for $z = 0$. The state of firms shifts around according to the Brownian motion. There is also an outflow due to mergers, $\mu f_S(z)$, and rescaling of the density due to growth $g f_S(z)$. At $z = 0$, due to the inflow of new entrants, equation 5 no longer describes the dynamics of the startup firms. We impose continuity of the density at this point. The conditional distribution of startups follows a familiar double-Pareto distribution. This features a thinner tail of the startup firm size distribution than a standard endogenous growth model with a fixed g, due to the possibility of acquisition. We omit the details of the closed-form solution in Lemma 5 in the Appendix. Figure 2 shows a numerical example of these densities. The mode of startup firm productivity is the entry point, $z = 0$. To its right, the density decays, as it requires more positive productivity shocks to reach higher levels of z. Similar logic implies a decreasing density at $z < 0$. At the exit threshold, the density has zero value and zero slope.

The overall distribution f includes platform products as well as startups. This distribution has a KFE:

$$0 = \frac{\nu^2}{2} f''(z) - g f(z),$$

for all points except for $z = 0$ and $z = z_S$. The KFE does not describe the law of motion at $z = 0$ because of entry, similar to the startup distribution. The KFE does not describe the law of motion at the startup exit point z_S because the startups and the platform have different shutdown thresholds.

This density also has a closed-form solution, which is summarized in the Lemma 6 in the Appendix. Figure 2 also shows an example of this density. The shape of the overall density of firm productivity resembles $f_S(z)$, with the difference that the lower bound of the support becomes the platform-owned firms' threshold, z_P.

Lastly, there is a unique population ratio for platform-owned firms and startups that guarantees stationarity. This ratio is summarized in the following Lemma.

Lemma 3 (Platform Share of Products) *On a balanced growth path, the platform's share of all products is given by*

$$\frac{N_P}{N} = 1 - \frac{\zeta_P^2}{\zeta_S^2} \frac{1 - e^{\zeta_S z_S}}{1 - e^{\zeta_S z_S} + e^{\zeta_P z_P} \left(e^{z_S(\zeta_S - \zeta_P)} - 1 \right)}.$$

The stationary distribution of platform-owned firms can be solved using the relationship $f(z) = \frac{N^P}{N} f_P(z) + \left(1 - \frac{N^P}{N}\right) f_S(z)$. We plot a numerical example in Figure 2. This density differs from $f(z)$ and $f_S(z)$ in that it is differentiable at $z = 0$, which reflects the assumption that entrants must be startups.

3.4 Definition and Characterization of BGP

A balanced growth path is a collection of value functions, exit thresholds, density of firms, and aggregates. Jointly, they satisfy the household's optimality, the firms' optimality, the market clearing conditions, and the stationarity conditions. We defer this formal definition to the Appendix. In the main text, we focus on the characterization of a BGP. Our model is tractable, in that a BGP can be characterized by first solving for the growth rate g and the ecosystem dominance ι_P. This is a problem of solving for two unknowns given two non-linear equations. All other endogenous variables can be thus solved for given (g, ι_P).

Propositon 1 *The BGP growth rate and ecosystem dominance solve equation (3) and (4).*

Intuitively, the BGP can be analyzed by interactions between decisions and general equilibrium forces. Taking as given its ecosystem dominance, the platform chooses the optimal tying, which implies the profits for startups and platform-owned firms. Firms, given these profits, decide on their optimal entry and exit decisions, which are summarized by the free-entry condition (3) and the exit thresholds. These thresholds manifest into the stationary distribution of firm productivities, which in turn determines the BGP ecosystem dominance in (4).

3.5 Efficiency Properties and Optimal Policy

Consider a planner who chooses consumption, platform use, entry, exit, and tying to maximize the discounted utility of the representative household. The formal definition of this planner's problem is provided in the Appendix. The following discussion aims to understand the distortions through four channels: (a) platform under-utilization, (b) aggregate productivity, (c) growth effects, and (d) markup distortions,

Platform Under-utilization We start by detailing the static decisions of the planner, given the distributions $f(z)$ and $f_S(z)$, the platform share $\frac{N_{P,t}}{N_t}$, the total number of varieties N_t, and the average quality $\bar{Z}_t$. The optimal consumption choice implies an efficient labor productivity $Z^*(t)$:

$$Z^*(t) = \underbrace{(\bar{Z}_t N_t)^{\frac{1}{\sigma-1}}}_{\text{Agg. Quality}} \times \underbrace{(1 + \Phi_t \Delta - \Phi_t \delta(1 - \iota_{P,t}))^{\frac{1}{\sigma-1}}}_{\text{Agg. Platform Complementarity}}.$$

From this labor productivity, the optimal tying choice of the planner is to set $\delta(t) = 0$ and $\Phi(t)$ according to the same first order condition as in the equilibrium:

$$\Phi(t) = \left(\frac{1}{(\sigma - 1)} - \frac{1}{\Delta} \right).$$

Notice that platform use doubles compared to the competitive equilibrium, since tying caused households to under-utilize the platform in the decentralized economy.

Entry and Exit Dynamically, the planner values a product according to its social value $v^*(z)$, which includes knowledge spillovers to the creation of other new products as in Romer (1990):

$$(\rho + g)v^*(z) = \frac{e^z}{\sigma - 1} - f + \frac{\nu^2}{2} v^{*''}(z).$$

Similar to the choice of shutdown threshold for platform firms, the planner's shutdown threshold z^* :

$$e^{z^*} = \left(1 - \frac{1}{\eta^*}\right) \frac{f}{\pi^*}$$

where $\eta^* = \eta_P$ and $\pi^* = 1$.

Given the same growth rate, the planner would set a lower exit threshold for the startups and could set a higher or lower threshold for platform product lines depending on whether tying (which lowers the platform exit threshold) or lack of appropriability (which raises the platform exit threshold) dominates in the decentralized economy. The BGP growth rate for the planner solves:

$$\kappa(\sigma - 1) = \frac{1}{\rho + g - \frac{\nu^2}{2}} + \frac{\psi(\sigma - 1)}{\rho + g} \left(\frac{e^{\eta * z_P}}{1 + \eta^*} - 1\right).$$

This comparison implies that the social planner would set a lower exit threshold than the startups in the equilibrium. This disparity means the equilibrium has too much startup exit.

Markup. The static choice of production labor equalizes the marginal utility from consumption to the marginal utility of labor, and thus:

$$L_P^* = 1.$$

3.6 Welfare Decomposition on Balanced Growth Path

Given any balanced growth path with growth rate g and ecosystem dominance ι_P, letting e denote the steady state entry rate, the household's discounted utility can be decomposed into four terms (ignoring operating costs which are the same on any BGP)

$$\rho \mathcal{W} = W_g + W_p + W_z + W_m.$$

This decomposition is useful for understanding the different forces at play when we evaluate counterfactual policies in section 4. $W_g = \frac{g}{\rho} - \kappa e$ captures the "innovation efficiency" of the economy, the amount of variety growth created net of churn (the entry rate times the entry cost). The "platform" term $W_p = \frac{1}{\sigma - 1} \log(1 + \Phi(\Delta - \delta(1 - \iota_z))) - \Phi$ is the consumption benefit of using the platform. This benefit is decreasing in tying, but tying is less important when ecosystem dominance is high. The platform term also accounts for the disutility of labor time spent using the platform.

Average productivity $W_z = \log \bar{Z}$ also positively affects steady state consumption. Finally, there is the standard markup distortion $W_m = -\log(\frac{\sigma}{\sigma-1}) - \frac{\sigma}{\sigma-1}$ with markups depressing output and thus production labor.

4 Quantitative Model

The calibration strategy proceeds in several steps. First, we take standard values for household preferences from the literature, setting $\rho = 0.03$ and $\sigma = 4$ (this implies firm-level markups of 33%, in line with the estimates of De Loecker, Eeckhout, and Unger (2020) and De Ridder, Grassi, and Morzenti (2024)). We also set the target's (startup's) bargaining power $\beta = 0.5$ as estimated by David (2020).

Second, we compute a "pre-platform" steady state of the model and calibrate the entry cost κ and fixed cost f to match an annual growth rate of 2% and entry rate of 11.6% that Luttmer (2007) uses as targets for the U.S. in 2002, where we also assume $\Delta = 0$, that is, there is no technological benefit of the platform yet. The volatility of the productivity process ν is set to 0.043 (Luttmer 2007).

Third, we compute a new "platform" steady state to calibrate the benefit Δ of using the platform. Our model measure of time spent on the platform is Φ^*. We take the data analog of this moment to be time spent online from Nielsen's (2021) by U.S. households.[10] U.S. households spent 3.8 hours per day online across computers, smartphones and tablets in 2021.[11]

The final parameter to calibrate is the merger 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 the platform supplies 8.7% of all products in the economy. Tying (plus productivity differences, though these are quantitatively small) means the platform captures 11% share of revenue. Table 2 summarizes the chosen parameters and Table 3 demonstrates the model fit for the pre- and post-platform economies.

[10] We could also consider labor inputs to producing the platform good, summing two measures of labor costs, cost of goods sold (COGS) and selling and general administrative expense (SGA), for GAFAM in Compustat and dividing by GDP. This gives a target of 0.11, implying a higher benefit of using the platform and a higher steady state platform use than the current calibration.

[11] Dividing this by 24 hours in a day and adjusting by the labor share 0.6 converts this to a share of GDP of 0.095.

	Value	Meaning
ρ	0.03	Discount rate (annual)
σ	4	Elas. of substitution
Δ	6.98	Platform technology
ν	0.043	Std. dev. prod. shock
ψ	0.384	Fixed cost
κ	3.12	Entry cost
μ	0.0019	Merger meeting rate
β	0.5	Entrant barg. power

Table 2: Model parameters, baseline.

4.1 Welfare effects of the platform in decentralized economy

In the pre-platform steady state (Table 3 column 2) there is no technological benefit of the platform so it does not engage in product tying. There are no differences between the platform and standalone firms in terms of output or profits conditional on productivity. The shutdown thresholds for unprofitable product lines are the same for the platform and standalone firms.

Through the introduction of the platform (Table 3 column 3) and resulting time use on the platform, consumers generate additional consumption benefits equal to 1.7% consumption equivalent each period. However, the platform now engages in product tying. Flow profits for a standalone firm are only $\frac{1+\Phi^*(\Delta-\delta^*)}{1+\Phi^*(\Delta)} \times 100 = 82.5\%$ of platform profits for a product with the same productivity z. This raises the shutdown threshold z_S for standalone firms and lowers the shutdown threshold z_P of the platform. On net this raises the annual exit rate by nearly 2 percentage points. Platform tying depresses the growth rate (equal to net entry) by 0.1 percentage points. These two forces, churn and lower net entry, make the economy less efficient in creating new varieties. Introducing the platform results in an overall welfare loss.

4.2 Policy experiments

Section 3.5 showed that banning tying is part of implementing the first best allocation (along with correcting markups and lack of appropriability). Table 4 shows the changes in growth, exit, platform use, and welfare that result from a policy to ban ty-

	Data	Pre-plat.	Plat.
growth rate	0.020	0.021	0.020
entry rate	0.116	0.117	0.132
exit rate	0.096	0.096	0.112
platform time use	0.095	0.000	0.095
platform rev. share	0.110	0.087	0.109
tying $\frac{\delta}{\Delta}$	-	0.000	0.439
startups cutoff, z_S	-	-1.102	-1.088
platform cutoff, z_P	-	-1.102	-1.277
Welfare, CE % chg.	-	-	-6.7
platform	-	-	1.7
innov. eff.	-	-	-8.7
other	-	-	0.3

Table 3: Model fit for targeted moments, features of model steady, and welfare effects of introducing a platform with the value of Δ in Table 2. CE = consumption equivalent. See section 3.6 for more details on welfare components.

ing. Such a policy (Table 4 column 2) eliminates differences in profits for the platform and standalone firms for a given product, restoring the higher growth rate and lower churn of the pre-platform equilibrium (Table 3 column 2) and results in substantial welfare gains in terms of innovation efficiency. Moreover, using the platform now generates appeal 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. It's not clear how to ban tying in practice since it is often hard to detect. Empirically, Waldfogel (2024) finds that Europe's Digital Markets Act reduced Amazon's self-preferencing in search ranks from 30 ranks to 20 ranks.

Since acquisitions strengthen the ecosystem dominance of the platform and raise tying, an alternative way to reduce tying is to reduce the platform's share of products in equilibrium by banning acquisitions. The platform's tying decision problem is not well defined when its profits are zero, so the specific policy we consider sets the merger meeting rate μ to a very small positive number such the platform's steady state revenue share is close to, but not exactly, zero. This modestly reduces tying, and

	Plat.	$\delta = 0$	$\mu \approx 0$
growth rate	0.020	0.021	0.021
entry rate	0.132	0.117	0.142
exit rate	0.112	0.096	0.121
platform time use	0.095	0.190	0.095
platform rev. share	0.109	0.087	0.000
tying $\frac{\delta}{\Delta}$	0.439	0.000	0.399
startups cutoff, z_S	-1.088	-1.102	-1.102
platform cutoff, z_P	-1.277	-1.102	-1.275
Welfare, CE % chg.	-	15.8	0.5
platform	-	7.4	0.0
innov. eff.	-	8.7	0.8
other	-	-0.3	-0.3

Table 4: Features of model steady state with no policy interventions ("Plat."), a policy banning tying ($\delta = 0$), or a policy blocking nearly all acquisitions ($\mu \approx 0$). CE = consumption equivalent. See section 3.6 for more details on welfare components.

restores the exit threshold z_S to its pre-platform value and raises the growth rate. This results in a consumption equivalent welfare gain of 0.5% every period compared to the 15.8% gain from eliminating tying.

Figure 3 shows how various steady state moments change as the merger meeting rate changes to further illustrate the policy implications of reducing the merger rate. Fewer mergers reduce the ecosystem dominance of the platform by reducing the platform's share of goods. This reduces the platform's optimal tying since startup goods become more important for household's choice of platform use as the platform's share of goods falls. The most important outcomes are the entry rate and the growth rate. Lower tying encourages entry as the merger meeting rate falls, and this increases the growth rate.

5 Conclusion

Platform firms intermediate a rapidly growing share of total consumption. We present a new model to understand how platform-based consumption affects firms' incentives

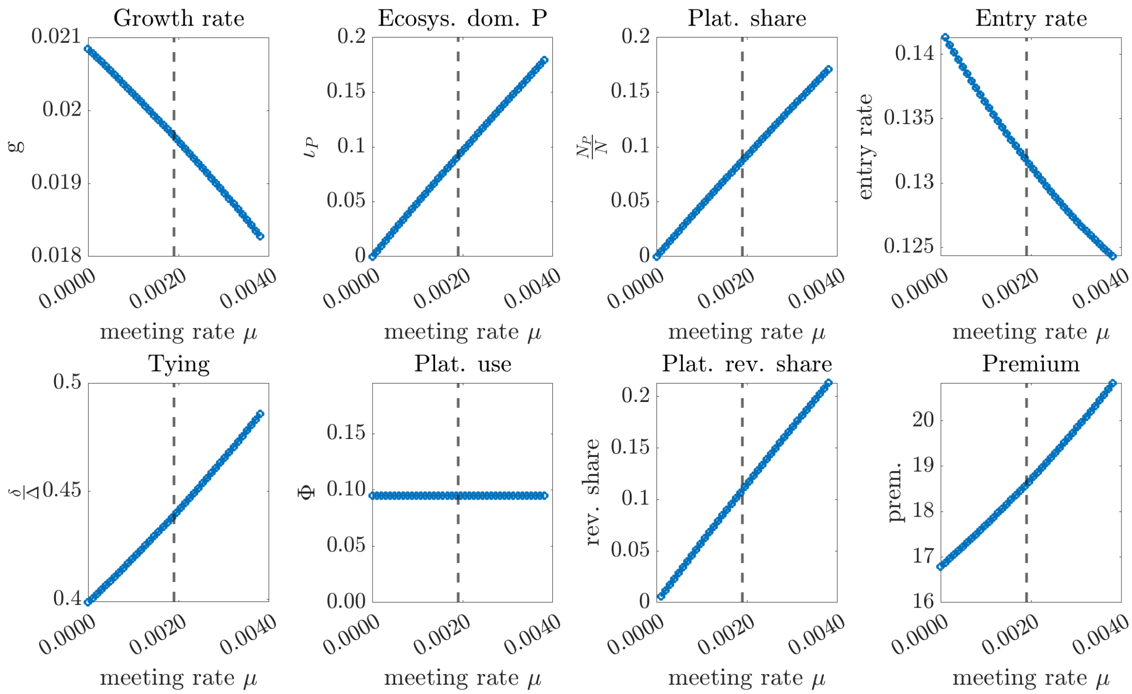

Figure 3: Comparative statics for the merger meeting rate. Each point is a different balanced growth path with a different value of μ.

to create new products to be sold on the platform when the platform can engage in product tying and acquire third party sellers through mergers. We match time use online and the revenue share of platforms in the U.S. to quantify the model and show that the welfare gains to banning tying (or equivalently requiring interoperability) are potentially large. Acquisitions increase the extent of tying, so reducing the acquisition rate of Big Tech firms can modestly improve welfare, but these gains are significantly smaller.

The new framework is quite rich. One question for future work is how the creation of the platform technology, Δ, interacts with merger policy and broader antitrust policy that limits 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 Model Appendix

Lemma 4 (Value Function) *On a balanced growth path, the equilibrium value of firms are given by the following equations:*

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

and

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

A.1 Proof of Lemma 1

We directly verify the equations in the lemma satisfy the value matching and smooth pasting conditions.

Lemma 5 (Startup Productivity Distribution) *The conditional distribution of startup productivity is*

$$f_S(z) = \epsilon_0 \times \begin{cases} e^{-\zeta_S z} & z \geq 0 \\ \frac{e^{\zeta_S z} - e^{-\zeta_S (z - 2z_S)}}{1 - e^{2\zeta_S z_S}} & z < 0, \end{cases}$$

where $\epsilon_0 = \frac{\zeta_S (1 + e^{\zeta_S z_S})}{2}$ *and* $\zeta_S = \left(\frac{g+\mu}{\nu^2/2}\right)^{1/2}$.

A.2 Proof of Lemma 2

We directly verify the proposed solution satisfy the KFE as well as four conditions:

1. (Integratability) $\lim_{z\to\infty} f_S(z) = 0$
2. (Continuity) $f_S+(0) = f_S-(0)$
3. (Zero density) $f_S(z_S) = 0$
4. (pdf) $\int_{z_S}^{\infty} f_S(z)dz = 1$

Lemma 6 (Economy-wide Productivity Distribution)

$$f(z) = \begin{cases} f_0 e^{-\zeta_P z} & z > 0 \\ f_1 \left(e^{\zeta_P z} + e^{-\zeta_P z} f_2\right) & z \in [z_S, 0] \\ f_3 \left(e^{\zeta_P z} - e^{-\zeta_P (z - 2z_P)}\right) & z < z_S, \end{cases}$$

where $f_0 = \frac{\zeta_P\left(1+e^{(\zeta_S-\zeta_P)z_S+2\zeta_P z_P}-e^{2\zeta_P z_P}-e^{z_S(\zeta_S+\zeta_P)}\right)}{2\left(1+e^{(\zeta_S - \zeta_P)z_S+\zeta_P z_P}-e^{\zeta_P z_P}-e^{z_S\zeta_S}\right)}$, $f_1 = \frac{\zeta_P}{2\left(1+e^{z_S(\zeta_S-\zeta_P)+\zeta_P z_P}-e^{\zeta_P z_P}-e^{\zeta_S z_S}\right)}$, $f_2 = \left(e^{z_S(\zeta_S-\zeta_P)+2z_P\zeta_P} - e^{(\zeta_S+\zeta_P)z_S} - e^{2\zeta_P z_P}\right)$, $f_3 = \frac{\zeta_P\left(1-e^{(\zeta_S-\zeta_P)z_S}\right)}{2\left(1+e^{z_S(\zeta_S-\zeta_P)+\zeta_P z_P}-e^{\zeta_P z_P}-e^{\zeta_S z_S}\right)}$, *and* $\zeta_P = \left(\frac{g}{\nu^2/2}\right)^{1/2}$.

A.3 Proof of Lemma 3

Because this distribution is segmented into three, to pin down a particular solution, we need to solve for six unknowns. Together with the equation for $\frac{N_P}{N} = 1 - \frac{N_S}{N}$, we impose the following conditions

1. (Integratability) $\lim_{z\to\infty} f(z) = 0$
2. (Continuity) $f_+(0) = f_-(0)$
3. (Continuity) $f_+(z_S) = f_-(z_S)$
4. (Zero density) $f(z_P) = 0$
5. (pdf) $\int_{z_P}^{\infty} f(z)dz = 1$
6. (Differentiability of $f(z)$) $\lim_{z\to 0^-}\left[f'(z) - \frac{N_S}{N} f_S(z)\right] = \lim_{z\to 0^+}\left[(1+\alpha)f'(z) - \frac{N_S}{N} f_S(z)\right]$
7. (Flow balance) $\frac{N_S}{N}\mu = (1 - \frac{N_S}{N})g + \frac{\nu^2}{2}'(z_P)$

B Data Appendix

B.1 Summary Statistics for Acquisitions

Summary statistics for Big Tech acquisitions are in Table 5. The GAFAM group did 133 acquisitions per firm from 2010-2020, more than the other three groups, giving us 665 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 merger 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 four publicly listed targets. GAFAM firms were more likely to acquire young firms, even controlling for average firm age in the same industry. Targets of GAFAM had more patents relative to targets of other acquirers as well as relative to other firms in their industry. On the other hand they were less likely to have positive earnings before interest, taxes, depreciation, and amortization (EBITDA) or pre-tax income in the 12 months prior to acquisition than targets of other firms.

B.2 Evidence for Random Search

One concern is that acquirers, particularly platforms, 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.[12] This gives us 119 target firms. 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.

[12] It is difficult to measure startup quality for startups without patents. Table 5 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. However these measures do not account for intangible intensity or other quality measures of interest.

	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, %	68.7	59.4	48.9	49.4
Merger 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 5: 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 (2022): the largest non-GAFAM acquirers labelled as high-tech by Forbes' ranking of Top 100 Digital Companies ("Top 25 Hi-Tech"), the largest private equity firms by Private Equity International ("Top 25 PE") and the other largest 25 firms by number of acquisitions in the S&P database ("Top 25 S&P").

2. Other patenting firms in the USPTO PatentsView data (yields 909 control firms on average) with:
   - Cosine similarity $\theta_{ij} > 0.9$, 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, 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).