Platform Acquisitions, Tying, and Growth*

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Abstract

To understand competition in digital industries, we develop a growth model of consumption through a platform. The platform owns some of the products in the economy and the rest are operated 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, platform use, growth, and welfare. The platform has an ambiguous effect on entry: the option value of acquisition encourages entry, while tying discourages entry 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.

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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 (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 platform technologies (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 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).

[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).

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 Recent Trends

We first use data from SDC Platinum to document that Big Tech firms have acquired targets in a large, 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 fuzzymatching 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 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.

Most acquisitions by Big Tech are cross industry, regardless of the way we define an industry (Table 1). The most conservative definition, the SDC Platinum's own classification scheme for high tech firms, gives a cross-industry share of 69%. Using 6-digits NAICS gives a cross-industry share of 83%. Comparing Big Tech to other large acquirers shows that Big Tech firms are *more* likely to engage in cross industry acquisitions compared to other acquirers. These findings are consistent with previous evidence (Argentesi et al. 2020; Parker, Petropoulos, and Alstyne 2021; Jin, Leccese, and Wagman 2022; Jin, Leccese, and Wagman 2023) that only a small fraction of firms acquired by GAFAM operated a platform or other competing service.

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 2010-2020.

	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").

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 expanding.[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. On the other hand Big Tech firms do not just sell to final consumers ("B2C") they also sell their services, such as Microsoft Office or Ama-

[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.

zon Web Services, to other firms ("B2B") which is missed in retail sales. To address this, we take total revenue of GAFAM in Compustat divided by total U.S. non-farm, non-financial revenues, which results in a revenue share of 11% in 2021. Compustat, drawing on firm 10-Ks, uses global sales and allocates sales across only a few business segments that do a poor job capturing different business lines (Hoberg and Phillips 2024). On the other hand this estimate conservatively measures platforms only as the five Big Tech firms. We maintain the focus on GAFAM to match regulations in US, UK, and EU that also focus exclusively on these five firms.

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 these firms are all among the top ten firms expected to contribute the most to future earnings growth. As of July 2024 these five companies make up 27% of the S&P 500 by market capitalization.

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.[5]

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 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, there are N_t of these products, with an index $i \in [0, N_t]$. 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 constant elasticity of substitution (CES) demand system is otherwise identical to the ones in the litera-

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

ture, except for an explicit model of platform usage through appeal $\phi_i(t)$. This appeal depends on whether product i is belongs to the platform:

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

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 Φ_t (for example, network effects) in terms of labor time. Platform usage comes from the household's optimal choice.

Goods produced by standalone firms, who we refer to as startups, enjoy only some of the benefits of platform usage. The platform chooses δ_t, which represents a wide range of behaviors it 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, reduce the performance of third party apps on their platform to privilege their own apps.[6] We use δ_t to encompass all such behavior.

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 the entry and exit decisions of startups. There is a large measure of potential entrants who can create a new startup by paying a labor cost of $\frac{\kappa}{N_t Z_t}$ where Z_t denotes average productivity of all goods at time t. To generate exit dynamics, we assume operating a product line incurs an operating cost of $\frac{f}{N_t Z_t}$ and productivity is stochastic. New entrants start with a 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 $\frac{f}{N_t Z_t}$ 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. In Appendix B.2 we provide evi-

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

dence in favor of the assumption of random search, 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. The two parties then decide on whether to merge. Upon merging, the startup claims β share of the joint surplus while the platform claims $1-\beta$ share of the joint surplus.

3.1 Static Equilibrium

Pricing Equilibrium. We start by characterizing the pricing equilibrium among firms, conditional on the aggregate platform usage Φ_t and the productivity distribution $f(z)$ of all products in the economy. The optimal pricing equilibrium implies that all firms, including the platform, charge a constant markup on their marginal costs: $p_i(t) = \frac{\sigma}{\sigma-1} e^{z_i(t)/(1-\sigma)}$. Using this optimal price, we derive the aggregate price index of this economy

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

where $\iota_{P,t} = \frac{N_{P,t}}{N_t} \frac{\bar{Z}_{P,t}}{\bar{Z}_t}$ measures the relative productivity of platform owned goods to the economy. We refer to $\iota_{P,t}$ as the "ecosystem dominance" of the platform, where dominance comes either from supplying a large share of all products, or from having higher average productivity. 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:

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

and

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

Platform use and tying decision 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 $P_t C_t = 1$ 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:

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

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 choice yields an expression that is independent of ecosystem dominance,[7]

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

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.

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

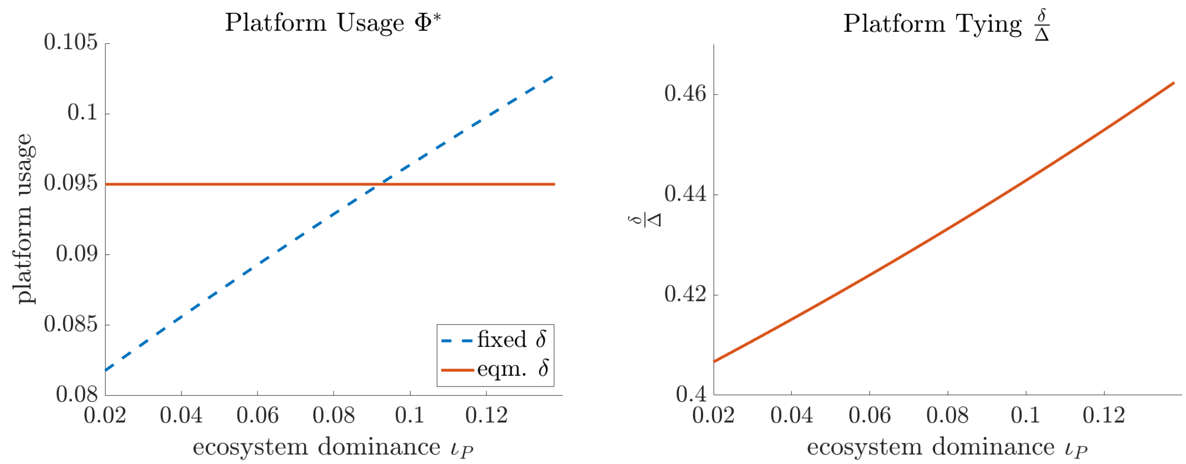

Figure 1: Household platform use and platform tying as a function of platform ecosystem dominance ι_P. Orange lines show equilibrium values and blue line shows counterfactual where tying is fixed at its baseline value and ecosystem dominance varies exogenously.

3.2 Dynamic Equilibrium

Growth in this economy comes the creation of new products (entry net of exit). To characterize the entry-exit decisions of firms on a balanced growth path with growth rate g, we start by characterizing the value of product lines, 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) as $v_S(z)$ and the value of a single platform product line as $v_P(z)$, both as functions of productivity z. Conditional on operating, the platform product line's value evolves according to the following Bellman equation:

$$(\rho + g)v_P(z) = e^z \pi_P - f + \frac{\nu^2}{2} v_P''(z),$$

and there is a shutdown threshold z_P for a platform product such that $v_P(z_P) = 0$ (the value matching condition) and $v_P'(z_P) = 0$ (the smooth pasting condition). We have used the fact that both profits and fixed costs f scale in $N\bar{Z}$.

Similarly, a startup has the Bellman equation

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

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.

In the following Lemma, we show that both value functions can be solved in closed form and the exit thresholds are solutions to two algebraic equations.

Lemma 1 (Value Functions) *On a balanced growth path, the equilibrium value of firms are given by the following equations:*

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

and

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

where $\eta_P = \left(\frac{\rho + g}{\nu^2/2}\right)^{1/2}$ *and* $\eta_S = \left(\frac{\rho + g + \mu\beta}{\nu^2/2}\right)^{1/2}$. *The exit thresholds are solutions to the following equations*

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

and

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

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.

3.3 Balanced Growth Path

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.

On a balanced growth path, consistent with free entry, 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:

$$\kappa\sigma = v_P(0) - \frac{\pi_P - \pi_S}{g + \rho + \mu\beta - \frac{\nu^2}{2}} - e^{\eta_S z_S}\left(v_P(z_S) - \frac{\pi_P - \pi_S}{g + \rho + \mu\beta - \frac{\nu^2}{2}} e^{z_S}\right).$$

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

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

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 the growth effect $g f_S(z)$. This equation does not describe the movement at $z = 0$ because that is the entry point of new firms. We show in Appendix A that $f_S(z)$ has a closed form solution, summarized in the following lemma.

Lemma 2 (Startup Productivity Distribution) *The conditional distribution of startup productivity is*

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

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

The conditional distribution of startups follows a familiar double-Pareto distribution. This features a thinner tail of the startup firm size distribution than in (Luttmer 2007) due to the possibility of acquisition.

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.

We show in the following lemma that this distribution has a closed form as well, although the formulas are more involved.

Lemma 3 (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* $\zeta_P = \left(\frac{g}{\nu^2/2}\right)^{1/2}$.

Lemma 4 (Platform Share of Products) *On a balanced growth path, the platform's share of all products is given by*

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

Although the distributions are complex, they lead to a simple aggregation of steady state ecosystem dominance ι_P

Lemma 5 (Relative Productivity) *On a balanced growth path, the platform's ecosystem dominance is given by*

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

3.4 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.

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 $\delta = 0$ and Φ according to the same first order condition as in the equilibrium:

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

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

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

$$L_P^* = 1.$$

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

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

3.5 Welfare Decomposition on Balanced Growth Path

Given any balanced growth path of growth rate g and 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 different 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.[8] U.S. households spent 3.8 hours per day online across computers, smartphones and tablets in 2021.[9]

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

[8]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.

[9]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.

parameters and Table 3 demonstrates the model fit for the pre- and post-platform economies.

	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
f	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.

	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 3.5 for more details on welfare components.

4.2 Policy experiments

Section 3.4 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 tying. 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 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.

	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 3.5 for more details on welfare components.

Figure 2 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.

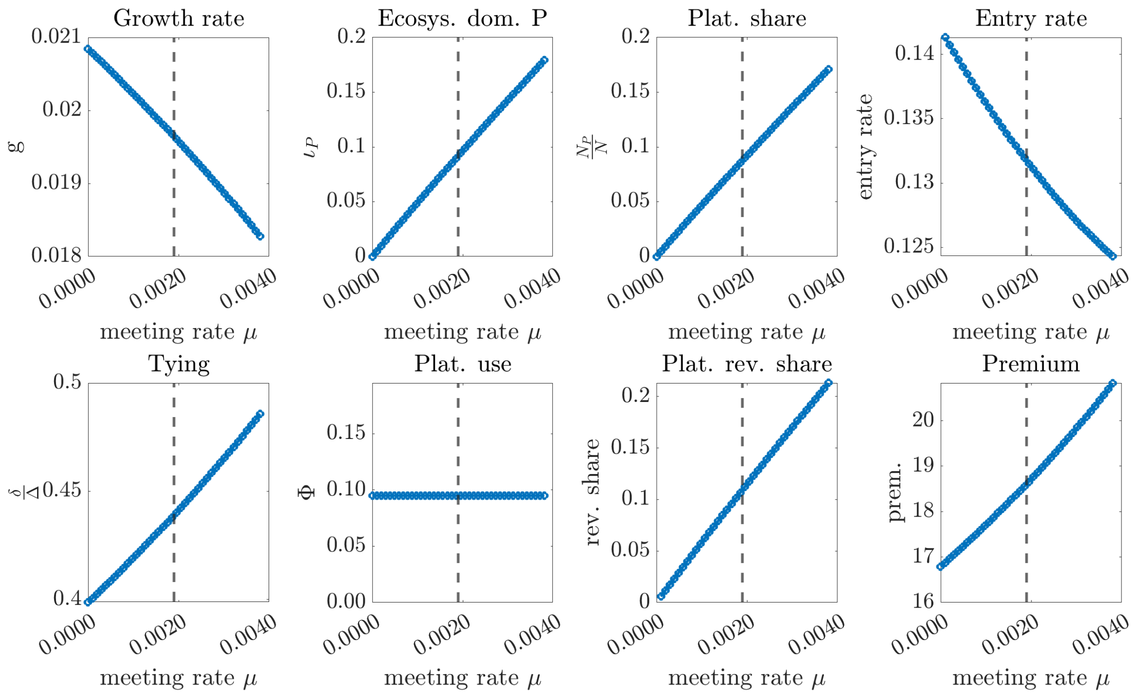

Figure 2: Comparative statics for the merger meeting rate. Each point is a different balanced growth path with a different value of μ.

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 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.

References

Akcigit, Ufuk, Murat Alp Celik, and Jeremy Greenwood. 2016. "Buy, Keep, or Sell: Economic Growth and the Market for Ideas." *Econometrica* 84 (3): 943–984.

Alvarez, Fernando, David Argente, Francesco Lippi, Esteban Mendez, and Diana Van Patten. 2023. "Strategic Complementarities in a Dynamic Model of Technology Adoption: P2P Digital Payments."

Argentesi, Elena, Paolo Buccirossi, Emilio Calvano, Tomaso Duso, Alessia Marrazzo, and Salvatore Nava. 2020. "Merger Policy in Digital Markets: An Ex Post Assessment." *Journal of Competition Law and Economics* 17 (July): 95–140.

Baslandze, Salome, Jeremy Greenwood, Ricardo Marto, and Sara Moreira. 2023. "The expansion of varieties in the new age of advertising." *Review of Economic Dynamics* 50:171–210.

Bhandari, Anmol, Ellen McGrattan, and Paolo Martellini. 2022. "A Theory of Business Transfers."

Bhandari, Anmol, and Ellen R McGrattan. 2020. "Sweat Equity in U.S. Private Business." *The Quarterly Journal of Economics* 136 (2): 727–781 (12).

Blonigen, Bruce A., and Justin R. Pierce. 2016. "Evidence for the Effects of Mergers on Market Power and Efficiency." *Finance and Economics Discussion Series 2016-082*, p. 35.

Boppart, Timo, Pete Klenow, Huiyu Li, and Reiko Laski. 2024. "Idea Rents and Firm Growth."

Bryan, Kevin, and Erik Hovenkamp. 2020. "Antitrust Limits on Startup Acquisitions." *Review of Industrial Organization* 56 (4): 615–636.

Brynjolfsson, Erik, Long Chen, and Xijie Gao. 2022, December. "Gains from Product Variety: Evidence from a Large Digital Platform." Working paper 30802, National Bureau of Economic Research.

Cabral, Luís. 2021. "Merger policy in digital industries." *Information Economics and Policy* 54:100866.

Cavenaile, Laurent, Murat Alp Celik, Jesse Perla, and Pau Roldan-Blanco. 2023. "A Theory of Dynamic Product Awareness and Targeted Advertising."

Celik, Murat Alp, Xu Tian, and Wenyu Wang. 2022. "Acquiring Innovation Under Information Frictions." *The Review of Financial Studies* 35 (10): 4474–4517 (1).

Chatterjee, Satyajit, and Burcu Eyigungor. 2023. “The Firm Size-Leverage Relationship and Its Implications for Entry and Business Concentration.” *Review of Economic Dynamics* 48, no. April.

Choi, Jay Pil. 2010. “Tying in Two-Sided Markets with Multi-homing.” *The Journal of Industrial Economics* 58 (3): 607–626.

Cunningham, Colleen, Song Ma, and Florian Ederer. 2020. “Killer Acquisitions.” *Journal of Political Economy* 129, no. 2.

David, Joel M. 2020. “The Aggregate Implications of Mergers and Acquisitions.” *The Review of Economic Studies* 88 (4): 1796–1830 (11).

De Loecker, Jan, Jan Eeckhout, and Gabriel Unger. 2020. “The Rise of Market Power and the Macroeconomic Implications.” *The Quarterly Journal of Economics* 135 (2): 561–644 (01).

De Ridder, Maarten, Basile Grassi, and Giovanni Morzenti. 2024. “The Hitchhiker’s Guide to Markup Estimation: Assessing Estimates from Financial Data.”

Ederer, Florian, and Bruno Pellegrino. 2023. “The Great Start-up Sellout and the Rise of Oligopoly.” *AEA Papers and Proceedings* 113 (May): 274–78.

Eisfeld, Luise. 2023. “Entry and Acquisitions in Software Markets *.”

Evans, David S., and Richard Schmalensee. 2013. “The Antitrust Analysis of Multi-Sided Platform Businesses.” *NBER Working Paper*, no. 18783.

Fons-Rosen, Christian, Pau Roldan-Blanco, and Tom Schmitz. 2024. “The Aggregate Effects of Acquisitions on Innovation and Economic Growth *.”

Fumagalli, Chiara, and Massimo Motta. 2020. “Tying in evolving industries, when future entry cannot be deterred.” *International Journal of Industrial Organization* 73:102567.

Greenwood, Jeremy, Yueyuan Ma, and Mehmet Yorukoglu. 2024. “‘You Will:’ A Macroeconomic Analysis of Digital Advertising.” *The Review of Economic Studies*, 06.

Hoberg, Gerard, and Gordon Phillips. 2010. “Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis.” *Review of Financial Studies* 23 (10): 3773–3811.

Hoberg, Gerard, and Gordon M Phillips. 2024. “Scope, Scale and Concentration: The 21st Century Firm.” *Journal of Finance*, vol. Forthcoming.

Hopenhayn, Hugo, and Richard Rogerson. 1993. “Job Turnover and Policy Evaluation: A General Equilibrium Analysis." *Journal of Political Economy* 101 (5): 915–938.

Hopenhayn, Hugo A. 1992. "Entry, Exit, and firm Dynamics in Long Run Equilibrium." *Econometrica* 60 (5): 1127–1150.

Jin, Ginger Zhe, Mario Leccese, and Liad Wagman. 2022. "How Do Top Acquirers compare in Technology Mergers? New Evidence from an S&P Taxonomy." *NBER Working Paper*, no. 29642.

———. 2023. "M&A and technological expansion." *Journal of Economics & Management Strategy* Special Issue, no. n/a.

Jovanovic, Boyan, and Peter L Rousseau. 2002. "q-Theory of Mergers." *American Economic Review* 92 (2): 198–204.

Kamepalli, Sai Krishna, Raghuram Rajan, and Luigi Zingales. 2020. "Kill Zone." NBER.

Kaplow, Louis. 2021. "Horizontal merger analysis." *International Journal of Industrial Organization* 79:102714.

Kokkoris, Ioannis, and Tommaso Valetti. 2020. "Innovation Considerations with Horizontal Merger Control." *Journal of Competition Law and Economics* 16 (April): 220–261.

Liu, Ou. 2023. "The Dynamics of Firm Size Inequality : The Role of Acquisition and Innovation." pp. 1–69.

Luttmer, Erzo G. J. 2007. "Selection, Growth, and the Size Distribution of Firms." *The Quarterly Journal of Economics* 122 (3): 1103–1144 (08).

Mermelstein, Ben, Mark A Satterthwaite, and Michael D Whinston. 2020. "Internal versus External Growth in Industries with Scale Economies : A Computational Model of Optimal Merger Policy Volker Nocke." *Journal of Political Economy* 128, no. 1.

Morton, Fiona Scott. 2023. "Digital Market Act designations: the interoperability of Google Android." *bruegel working paper*, no. 34.

Motta, Massimo. 2023. "Self-preferencing and foreclosure in digital markets: theories of harm for abuse cases."

Motta, Massimo, and Martin Peitz. 2021. "Big tech mergers." *Information Economics and Policy* 54:100868. Antitrust in the Digital Economy.

Nielsen's. 2021. "The Nielsen Total Audience Report ."

OECD. 2023. "Theories of Harm for Digital Mergers." *OECD Competition Policy Roundtable Background Note*.

Parker, Geoffrey, Georgios Petropoulos, and Marshall Van Alstyne. 2021. "Platform mergers and antitrust." *Industrial and Corporate Change* 30 (September): 1307–1336.

Pearce, Jeremy G., and Liangjie Wu. 2023. "Brand Reallocation, Concentration, and Growth."

Phillips, Gordon M, and Alexei Zhdanov. "R&D and the Incentives from Merger and Acquisition Activity." *The Review of Financial Studies*, no. 1:34–78.

Rachel, Lukasz. 2024. "Leisure-Enhancing Technological Change."

Rasmusen, Eric. 1988. "Entry for Buyout." *The Journal of Industrial Economics* 36 (3): 281–299.

Renneboog, Luc, and Cara Vansteenkiste. 2019. "Failure and success in mergers and acquisitions." *Journal of Corporate Finance* 58:650–699.

Rhodes-Kropf, Matthew, and David T Robinson. 2008. "The Market for Mergers and the Boundaries of the Firm." *Journal of Finance* LXIII, no. 3.

Rochet, Jean-Charles, and Jean Tirole. 2003. "Platform Competition in Two-Sided Markets." *Journal of the European Economic Association* 1 (4): 990–1029 (06).

———. 2006. "Two-sided markets: a progress report." *The RAND Journal of Economics* 37 (3): 645–667.

Romer, Paul M. 1990. "Endogenous Technological Change." *Journal of Political Economy* 98, no. 5.

Seru, Amit. 2014. "Firm boundaries matter: Evidence from conglomerates and R&D activity." *Journal of Financial Economics* 111 (2): 381–405.

Stiebale, Joel. 2016. "Cross-border M&As and innovative activity of acquiring and target firms." *Journal of International Economics* 99:1–15.

Waldfogel, Joel. 2024. "Amazon Self-Preferencing in the Shadow of the Digital Markets Act." *NBER Working Paper*, p. 22.

Warg, Katarina. 2022. "The Acquisition Option and Startup Innovations."

Wollmann, Thomas G. 2019. "Stealth Consolidation: Evidence from an Amendment to the Hart-Scott-Rodino Act." *American Economic Review: Insights* 1 (1): 77–94 (June).

A Model Appendix

A.1 Proof of Lemma 1

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

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) $\int_{z_S}^{\infty} f_S(z)dz = 1$

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 $\left(\frac{\text{deal price}}{\text{pre-acq. price}} - 1\right) * 100$, 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.[10] 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.

[10] 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: $F_i = \{F_{i,CPC_1}, \dots, F_{i,CPC_{132}}\}$
        - 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).