Digital Platform Acquisitions and Growth*

Jane Olmstead-Rumsey Federico Puglisi Liangjie Wu

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Abstract

We document that many acquisitions of startups by digital platforms are of firms offering complementary rather than directly competing goods and services. This motivates an endogenous growth model of competition among startups vying to create new technologies in winner-take-all markets. An acquirer outside the industry can meet and acquire startups in order to accelerate the process of establishing market dominance through innovation. The presence of acquirers may therefore increase the arrival rate of new technologies, but has ambiguous effects on their expected quality. When project quality is known, acquirers may be more selective than startups to fund the project because of merger costs, but if project quality is still uncertain, acquirers are less selective because of their greater ability to establish market dominance.

*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, and John van Reenen for helpful discussions.

1 Introduction

Recent competition policy in many countries has focused on the role of acquisitions by large firms, in particular platform-based firms, in stifling growth. Policy proposals in the US, UK, and Europe have all singled out the "GAFAM" (Google, Amazon, Facebook, Apple, and Microsoft) group for additional scrutiny. In the U.S., the proposed Platform Competition and Opportunity Act (2021) considered banning most acquisitions by this group altogether.

What is known about the acquisition behavior of the GAFAM firms? Much of the debate, both academic and legislative, has focused on the negative effect of platform acquisitions on "nascent competitors", the so-called "killer acquisitions" channel (Cunningham, Ma, and Ederer 2020; Fons-Rosen, Roldan-Blanco, and Schmitz 2023). In this paper we document, consistent with previous micro evidence (Argentesi et al. 2020; 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. Instead most targets are high tech and offer *complementary* products or services. Policies that raise the cost of mergers or reduce the chance that platform mergers succeed would therefore primarily affect this type of acquisition.

Motivated by this fact, we propose a theoretical model of cross-industry acquisitions as a complement to existing studies of within-industry acquisitions by this group. The model builds on the expanding variety growth model of Romer (1990) such that growth is driven by the creation of new products and services through patent races. In the original Romer model, all intermediate producers have the same productivity. Our model instead features intermediate goods producers with heterogeneous productivity as in Koren and Tenreyro (2013) so that welfare depends both on the efficiency and speed with which new varieties are created and on the average productivity (equivalently, quality) of incumbent firms in the economy.

The model makes two key assumptions about startup firms. The first is that they are less likely than the acquirers to establish market dominance (that is, to win the patent race) for a product of the same quality. This assumption captures financial constraints that startups face (Beck and Demirguc-Kunt 2006; Aghion, Fally, and Scarpetta 2007) and the idea that acquirers, particularly platform firms, are better positioned to scale startups ideas due to complementary technologies, existing customer bases, managerial efficiencies, or greater R&D efficiency (Bena and Li 2014). The second assumption is that a startup's quality is initially unknown and gets revealed over time. To support this assumption we show, using SDC Platinum's M&A database, that among firms acquired by GAFAM, 38% had negative earnings in the last 12 months and 50% had negative net income. 60% had no patents. GAFAM firms also acquire target firms that are 5-10 years younger than the targets of other large firms, even controlling for average firm age in the industries where acquisitions occur.

In the model, mergers require a one-time cost for the acquirer and search is random: acquirers randomly meet existing startups for possible merger. Platforms acquire startups of both known and unknown quality. A ban on platform-based mergers can be modelled as shutting off this meeting probability. Tighter scrutiny in the form of investigations, legal fees, and fines, can be captured with higher merger costs.

We show that mergers produce a potential tradeoff: they increase the rate at which new varieties are brought to market. However, it's also possible that they lower the average quality of products in the economy through selection effects. When platforms acquire a startup of unknown quality whose quality is eventually revealed to be low, they are more willing to continue financing this low quality venture because their greater chance of success in the patent race raises their expected profits compared to the startup. We call this a negative, post-merger selection effect. However, if a startup's quality is already known at the time a merger can take place, platforms may be *more* selective than startups about funding a project, since the merger is costly. We call this a positive pre-merger selection effect. So, the overall selection effect introduced by the presence of acquirers in the model has ambiguous sign. For acquisitions to negatively affect consumer welfare, it must be that the post-merger selection effect dominates the pre-merger selection effect and the positive effect on the creation of new products.

In future versions of the paper we plan to calibrate the model using data from the U.S. Census Business Dynamics Statistics, U.S. Patent Trademark Office, and SDC Platinum to quantitatively evaluate these three channels.

2 Related Literature

The literature has identified various motives for merger, such as q-theory motives (Jovanovic and Rousseau 2002); complementarities (Rhodes-Kropf and Robinson 2008; David 2020); acquiring innovation (Celik, Tian, and Wang 2022; Liu 2023) (relatedly Akcigit, Celik, and Greenwood (2016) study the market for patents); killer acquisitions (Cunningham, Ma, and Ederer 2020; Kamepalli, Rajan, and Zingales 2020; OECD

2020); and exploiting economies of scale (Mermelstein, Satterthwaite, and Whinston 2020). There is also a recent macro-growth literature studying the growth effects of acquisitions by large firms (Chatterjee and Eyigungor 2020; Cavenaile, Celik, and Tian 2021).

There is a vast empirical literature studying the effects of M&A on markups, innovation, productivity, and competition (Blonigen and Pierce 2016; Phillips and Zhdanov 2013; Ederer and Pellegrino 2023; Wollmann 2019; Eisfeld 2023; Seru 2014; Renneboog and Vansteenkiste 2019; Stiebale 2016; Hoberg and Phillips). 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 (Warg 2022; Fumagalli, Motta, and Tarantino 2020; Cabral 2021; Motta and Peitz 2020). Kaplow (2020) argues that a multi-sector, general equilibrium analysis is needed because of cross-industry distortions.

A final related strand of literature, beginning with Stiglitz and Weiss (1981), emphasizes the role of financial constraints on small firms in the growth process (Aghion, Fally, and Scarpetta 2007; Beck and Demirguc-Kunt 2006; Howell 2017; Caggese 2019).

3 Acquisitions by Digital Platforms

Our primary dataset is the SDC Platinum Database, which 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.

We document salient features of platform M&A by contrasting their acquisition activity with the acquisition activity of three other groups of large firms in the spirit of Jin, Leccese, and Wagman (2022), who perform a similar exercise using an S&P mergers dataset from 2010-2020. The three other groups are: 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"). The results are in Table 1.

The GAFAM group did 133 acquisitions per firm from 2010-2020, more than the other three groups, giving us 665 deals with which to assess deal and target charac-

	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 1: Source: SDC Platinum, 2010-2020, restricting attention to SDC-classified high tech targets. See text for details.

teristics of acquisitions by 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).[1] They also paid a significantly higher merger premium, defined as $\left(\frac{\text{deal price}}{\text{pre-acq. price}} - 1\right) * 100$. 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. 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

[1] The GAFAM firms operate in multiple segments and industries. In the next version of the paper we will use business segment data from 10-Ks to ensure targets are not operating in secondary, tertiary, etc. segments where GAFAM also operates.

one GAFAM acquisition, 2010-2020. We find that 55% of GDP and 25% of employment is in industries where GAFAM did at least one deal over this period.

4 Model

The model is populated by five types of agents: a representative household, incumbent intermediate good producers, a representative final good producer, startups vying to create new products through R&D, and an acquirer[2] who can buy startups and take over the R&D process, thus contributing to new product creation as well. We primarily focus our discussion on a balanced growth path (BGP) where output grows at rate g, though in computing welfare gains and losses from changes in merger rates we solve the full transition dynamics of the model from one steady state BGP to another.

4.1 Households

Households make a simple consumption savings choice according to:

$$\max_{C(t),\dot{A}(t)} \int_0^\infty e^{-\rho t} \log(C(t))dt,$$

subject to

$$C(t) + \dot{A}(t) \leq W(t)L + r(t)A(t).$$

This yields the standard Euler equation $r(t) = \rho + g(t)$.

4.2 Final Good Firms

The final goods sector is competitive. The representative firm uses labor and intermediate goods to produce final output $Y(t)$ with the following technology:

$$Y(t) = \frac{1}{1-\beta} L^\beta \int_0^{N(t)} x(i,t)^{1-\beta} di,$$

where $N(t)$ is the number of the existing intermediate good varieties at time t and β is the labor share.

[2]We consider the case of a single acquirer, though multiple acquirers do not change the results. This is because incumbent product lines and patent race projects all operate fully independently from one another. We later discuss relaxing this assumption.

We normalize the price of the final good to be 1. The final good producer also takes as given the price of intermediate inputs, $p(i,t)$. This gives a demand for intermediate input i:

$$x(i,t) = p(i,t)^{-1/\beta} L.$$

4.3 Incumbent Monopolists

Each intermediate producer i operates a linear technology using the final output, with productivity $\frac{z_i^{\frac{\beta}{1-\beta}}}{1-\beta}$. Thus the pricing problem of the intermediate producer is:

$$\max_p p(i,t)^{1-1/\beta} L - (1-\beta) z_i^{\frac{\beta}{\beta-1}} p(i,t)^{-1/\beta} L.$$

The optimal pricing decision implies that

$$p(i,t) = z_i^{\frac{\beta}{\beta-1}},$$

and

$$\pi(z) = \beta z L,$$

so that profits are increasing in z. The value of being a permanent monopolist with quality z is given by $r(t)V_m(z,t) = \beta z L + \dot{V}_m(z,t)$. Thus on the balanced growth path this value is $V_m(z) = \frac{\beta z L}{r} = \frac{\beta z L}{\rho + g}$.

4.4 New Variety Creation

At time t, a measure $\eta N(t)$ of new industries begin a patent race to develop that product line and establish market dominance as the perpetual incumbent monopolist in that industry.[3] Let τ index time within a patent race (rather than calendar time t). We first describe the problem of startups in the race, then the problem of the acquirer, and then describe the industry-shakeout style dynamics that the model generates.

4.4.1 Startups

Potential startups begin with a project of unknown quality, drawn from a known Pareto distribution $F(z)$ with lower bound $\underline{z}$ and tail index $\theta > 1$. We normalize the lower bound $\underline{z} = 1$. The quality of the project is revealed to the founders as well

[3] We later show that the value of entry on any new line is 0 or negative, so the number of patent races happening at any time is indeterminate unless we make this assumption.

as to the acquirer at rate ι, to capture the fact that the quality of young firms is often uncertain, even to the founders, and many targets are acquired with negative net income and no patents (Table 1).

Operating a startup requires a flow operating cost ϕ. This delivers an expected individual arrival rate of winning the patent race of λ_E. Define the industry-wide arrival rate as $\Lambda(\tau)$. The value of a startup of **revealed** quality z on the BGP is:

$$(r + \Lambda(\tau) + \lambda_E)V_E(z,\tau) = \lambda_E \frac{\beta z L}{r} - \phi$$

Firms shut down if their quality is revealed to be low enough such that expected discounted profits are less than operating costs. This defines a threshold z_E which is the lowest quality level at which a startup will continue operating:

$$z_E = \frac{r\phi}{\lambda_E \beta L}.$$

There is free entry into the patent races so that the expected value of entry is weakly negative in equilibrium, defining a free entry curve:

$$0 \geq V_0 \equiv \frac{\theta}{\theta-1}\frac{\lambda_E \beta \underline{z} L}{r} - \phi + \frac{\iota}{r + \Lambda(\tau) + \lambda_E} z_E{}^{-\theta}\left(\frac{\theta}{\theta-1}\frac{\lambda_E \beta z_E L}{r} - \phi\right). \tag{1}$$

The first time gives the expected value of winning the race for an entrant with unrevealed quality, since the expected quality of unrevealed entrants is $\frac{\theta}{\theta-1}\underline{z}$. At rate ι the startup's quality will be revealed. If $z < z_E$ the continuation value is 0. If $z \geq z_E$, which happens with probability $z_E^{-\theta}$, then the startup remains in the industry as a revealed quality startup.

4.4.2 Acquirer

An acquirer meets the existing startups for potential merger at rate μ. These can be projects with revealed or unrevealed quality. The acquirer captures all of the surplus from the merger (we discuss relaxing this assumption later on). A merger requires the acquirer to pay a one time cost $\chi \geq 0$, capturing legal fees, due diligence, and other costs associated with integrating the startup into the acquiring firm. The merged project has an arrival rate $\lambda_P > \lambda_E$ of winning the race due to the acquirer's enhanced capabilities of managing, undertaking, or commercializing innovation due stocks of data, customers, experience, etc. The flow operating cost for the project remains ϕ. If the acquired project is of unknown quality, its quality is revealed at rate ι. There is no limit to the number of projects the acquirer can acquire.

Given these assumptions, two more thresholds can be derived. The first is the shutdown threshold for a project whose quality is revealed after acquisition:

$$z_P = \frac{\phi}{\lambda_P \beta L}(\rho + g).$$

Notice that $z_p < z_E$ by $\lambda_P > \lambda_E$. This means that the acquirer has a negative post-merger selection effect, keeping worse projects running after their quality is revealed because of the acquirer's greater chance of success in the race. We make the assumption that $\frac{\theta}{\theta-1}\frac{\lambda_P \beta z L}{r} - \phi - \chi > 0$ so that the platform is willing to acquire unrevealed projects.

The second threshold is the threshold for acquisition of a project whose quality has already been revealed:

$$z_A = \frac{1}{\beta L}\left(\frac{\chi}{\lambda_P - \lambda_E}(\rho + g + \lambda_E)(\rho + g + \lambda_P) - \phi\right).$$

Whether this threshold is higher or lower than z_E depends on parameters, so this selection effect can be either positive or negative. Note that all three thresholds are t and τ invariant.

4.4.3 Industry Dynamics

At any point in the patent race, there are at most six types of projects in the industry. The first is unrevealed entrants with measure $\epsilon(\tau)$. The second is startups with quality below the acquisition threshold z_A but above the shutdown threshold z_E, $E_U(\tau)$ (if $z_A \leq z_E$ then this measure is obviously zero). The third is revealed entrants with quality above z_A such that they will be acquired if they meet the acquirer, $E_A(\tau)$. The fourth is unrevealed projects operated by the acquirer, $\psi(\tau)$. The fifth is revealed projects whose quality was revealed after acquisition to be below the pre-merger acquisition threshold z_A but nevertheless continue to operate because of the acquirer's funding advantage, $P_U(\tau)$. The last type are projects operated by the platform with quality above z_A, $P_A(\tau)$. These measures evolve according to the following flow equations:

$$\dot{E}_U(\tau) = \iota \left(\left(\frac{z_E}{\underline{z}} \right)^{-\theta} - \left(\frac{z_A}{\underline{z}} \right)^{-\theta} \right) \epsilon(\tau), \tag{2}$$

$$\dot{E}_A(\tau) = \iota \left(\frac{z_A}{\underline{z}} \right)^{-\theta} \epsilon(\tau) - \mu E_A(\tau), \tag{3}$$

$$\dot{\psi}(\tau) = \mu \epsilon(\tau) - \iota \psi(\tau), \tag{4}$$

$$\dot{P}_U(\tau) = \iota \left(\left(\frac{z_P}{\underline{z}} \right)^{-\theta} - \left(\frac{z_A}{\underline{z}} \right)^{-\theta} \right) \psi(\tau), \tag{5}$$

$$\dot{P}_A(\tau) = \iota \left(\frac{z_A}{\underline{z}} \right)^{-\theta} \psi(\tau) + \mu E_A(\tau), \tag{6}$$

$$\Lambda(\tau) = \lambda_E \left(E_U(\tau) + E_A(\tau) + \epsilon(\tau) \right) + \lambda_P \left(P_U(\tau) + P_A(\tau) + \psi(\tau) \right). \tag{7}$$

Equation 7 gives the aggregate arrival rate of a winning patent in the patent race. Note that, for a given g, there is a unique value Λ^* that sets the value of entry in Equation 1 to zero such that firms are indifferent about entering the race. For $\Lambda(\tau) > \Lambda^*$ the value of entry is negative and $\epsilon(\tau) = 0$. We make assumptions on parameters such that Λ^* is positive.[4] At the beginning of the race all innovation is done by unrevealed entrants such that $\Lambda(0) = \Lambda^* = \lambda_E \epsilon(0)$ and we therefore obtain the initial measure of entrants $\epsilon(0) = \frac{\Lambda^*}{\lambda_E}$. At any arbitrary τ,

$$\Lambda(\tau) = \max \left\{ \lambda_E \Big[E_U(\tau) + E_A(\tau) \Big] + \lambda_P \Big[P_U(\tau) + P_A(\tau) + \psi(\tau) \Big], \Lambda^* \right\}.$$

The expected quality of the winner of the patent race changes as the race unfolds. Setting aside acquisitions for a moment, consider an industry with only startups. The industry begins with only unrevealed entrants whose expected quality is $\frac{\theta}{\theta-1}$. As project quality is revealed, bad projects get shut down and more projects have expected quality $\frac{\theta}{\theta-1} z_E > \frac{\theta}{\theta-1}$. In general, the expected quality of the winner of the patent race is given by

$$Z(\tau) = \frac{\theta}{\theta-1} \frac{1}{\Lambda(\tau)} \left\{ \lambda_E \left(E_U(\tau) \frac{z_E^{1-\theta} - z_A^{1-\theta}}{z_E^{-\theta} - z_A^{-\theta}} + E_A(\tau) z_A + \epsilon(\tau) \underline{z} \right) + \right.$$
$$\left. + \lambda_P \left(P_U(\tau) \frac{z_P^{1-\theta} - z_A^{1-\theta}}{z_P^{-\theta} - z_A^{-\theta}} + P_A(\tau) z_A + \psi(\tau) \underline{z} \right) \right\}.$$

[4] Specifically, we focus on the case where $0 < \frac{\theta}{\theta-1} \frac{\lambda_E \beta \underline{z} L}{\rho} - \phi + \frac{\iota}{\rho+\lambda_E} \left(\frac{\rho\phi}{\lambda_E \beta L} \right)^{-\theta} \frac{1}{\theta-1} \phi$.

The platform's potential negative effect on quality can be seen in the comparison between the exit thresholds of revealed ventures operated by platforms and by entrants $\frac{z_P}{z_E} = \frac{\lambda_E}{\lambda_P}$. All else equal, the higher is λ_P relative to λ_E, the average quality of a revealed venture operated by platforms deteriorates compared to other ventures. This negatively affects the average quality of innovations.

Finally, we define the total mass of firms

$$F(\tau) = E_U(\tau) + E_A(\tau) + \epsilon(\tau) + P_U(\tau) + P_A(\tau) + \psi(\tau).$$

4.5 Aggregate Growth Rate on Balanced Growth Path

On the balanced growth path the number of varieties $N(t)$ grows at rate g. Denote the measure of races of duration τ at time t $M(\tau,t) = m(\tau)N(t)$, where $m(\tau)$ is the detrended measure of industries at τ which is constant over time. By assumption $m(0) = \eta$. The change in this measure with respect to τ is given by:

$$m'(\tau) = -(\Lambda(\tau) + g)m(\tau).$$

That is, $m(\tau)$ shrinks as $N(t)$ grows, plus there are outflows of races due to a firm winning the race, which happens at rate $\Lambda(\tau)$. Solving this ODE gives a formula for $m(\tau)$:

$$m(\tau) = \eta e^{-g\tau - \int_0^\tau \Lambda(s)ds}.$$

The growth rate is equal to the rate of creation of new varieties,

$$g = \eta \int_0^\infty e^{-g\tau - \int_0^\tau \Lambda(s)ds} \Lambda(\tau) d\tau. \tag{8}$$

Intuitively, this expression gives the expected arrival of new varieties over patent races of different durations, weighted by the likelihood that a race lasts until τ without concluding.

4.6 Steady State Productivity Distribution

Similar to the growth rate, we can find the average quality of incumbent varieties on the BGP by combining the $Z(\tau)$ formula with the probability that a race concludes at τ. First define the steady state fractions of projects of different types:

$$
\begin{aligned}
n_0 &\propto \int_0^\infty m(\tau)(\lambda_E \epsilon(\tau) + \lambda_P \psi(\tau)) d\tau, \\
n_{PU} &\propto \lambda_P \int_0^\infty m(\tau) PU(\tau) d\tau, \\
n_{PA} &\propto \lambda_P \int_0^\infty m(\tau) PA(\tau) d\tau, \\
n_{EU} &\propto \lambda_E \int_0^\infty m(\tau) EU(\tau) d\tau, \\
n_{EA} &\propto \lambda_E \int_0^\infty m(\tau) EA(\tau) d\tau.
\end{aligned}
$$

Such that average quality among the incumbent monopolists on the BGP is given by:

$$
z^* = \frac{\theta}{\theta - 1} \left(n_0 \underline{z} + (n_{PA} + n_{EA}) z_A + n_{PU} \frac{z_P^{1-\theta} - z_A^{1-\theta}}{z_P^{-\theta} - z_A^{-\theta}} + n_{EU} \frac{z_E^{1-\theta} - z_A^{1-\theta}}{z_E^{-\theta} - z_A^{-\theta}} \right).
$$

4.7 Welfare

On a balanced growth path where consumption at time t is given by $c^* e^{gt}$, where c^* is the detrended level of consumption, the households' lifetime utility of a particular path is given by

$$
U(c^* e^{gt}) = \frac{\log(c^*)}{\rho} + \frac{g}{\rho^2}
$$

The detrended level of consumption c^* can be obtained from the aggregate resource constraint:

$$
c^* = \left(\beta (1 - \beta)^{-\frac{1}{\beta}} z^* - \phi^* - \alpha^* \right) n^* L.
$$

where n^* is the detrended measure of existing varieties in steady state and $\phi* = \phi \int_0^\infty m(\tau) F(\tau) d\tau$ and $\alpha^* = \chi \mu \int_0^\infty m(\tau) [E_A(\tau) + \epsilon(\tau)] d\tau$. Finding the steady state detrended measure of varieties requires solving the full transition dynamics of the model (not just the industry dynamics). The solution algorithm for the full transition dynamics is described in Appendix A.2.

5 Discussion

5.1 Comparing Platforms to Traditional Acquirers

In the current version of the model, three parameters capture potential differences between an economy where traditional firms are the principle acquirers vs. one where platforms are the principle acquirers. As seen in Table 1, platforms tend to acquire younger firms. This can be proxied by a higher meeting rate μ. This could be because startups operate on the platform and thus are more likely to meet the platform for merger. However, operating on the platform might also convey more information about a startup's quality (for example Amazon buying firms that have high sales on its platform), modelled as a higher information revelation rate ι. Empirical evidence on this point is mixed: targets of platforms are more likely to have revealed quality as proxied by number of employees and patents, but less likely to have positive earnings prior to acquisition compared to targets of traditional firms. Finally, we observe that platforms pay a much higher premium for targets, which might suggest λ_P is higher or χ is lower for the platform firms, capturing a greater ability to scale the idea of the startups at low cost or integrate them into the platform's existing technological ecosystem.

5.2 Possible Extensions

The model is flexible enough to incorporate other theories of harm from platform mergers that the literature has identified. For example, it is easy to introduce a cutoff $z_{NC} > z_A$ such that the platform kills the project, proxying the nascent competitor theory. z_{NC} could be set such that a project with $z > z_{NC}$ would end up in the top 1% of incumbents by sales, for example.

Whether complementarities appear in the final product quality z or simply in the final profits, for example if $\pi(z) = \alpha\beta z L$ with $\alpha > 1$ for the platforms because of their monopoly power/customer base, matters for welfare because these have opposite effects on expected quality (at least in partial equilibrium).

We can also relax the assumption that the acquirers capture all of the merger surplus and introduce a bargaining power parameter $\gamma \in (0, 1)$. The option value of acquisition could then induce a negative selection effect on startups if $z_A < z_E$. Kamepalli, Rajan, and Zingales (2020) argue that platforms enjoy greater bargaining power than traditional firms because they can foreclose access to the platform and hurt the standalone profits of startups.

Another possible extension involves studying the startups' decision of whether to operate on the platform prior to acquisition. This decision would interact with the above mechanisms involving complementarities, meeting rates, information revelation, and bargaining power. One concern with platforms is their discouragement of "inter-operability": developing an app for the Google Play store and the Apple store both require effort because the ecosystems differ, so the operation choice could be extended to the case of multiple acquirers with different features and ecosystems competing for targets.

6 Illustrative Calibration

To demonstrate the model's key mechanisms we adopt an illustrative calibration with parameters given in Table 2 and present the patent race dynamics given these parameters. We then consider comparative statics for several of the model parameters and the welfare effects of changing the merger meeting rate μ, including welfare over the transition from one steady state to another.

The calibration is such that $z_A < z_E$ so that the platform's effect on the quality of new varieties is negative. To do this we set χ to 0. We quantitatively compare the negative selection effect to the greater efficiency with which the platform creates new varieties, as well as its effects on the steady state measure of incumbent varieties n^*.

6.1 Patent Race Dynamics

Figure 1 depicts the entry and acquisition dynamics of a patent race over time in the calibrated model. If the patent race takes long enough without a winner, industries settle down into a steady state with at most three types of projects: revealed startups with quality between z_E and z_A, revealed platform projects with quality between z_P and z_A, and revealed platform projects with quality above z_A. As bad entrants are revealed, they are shut down, though the presence of the platform dampens this effect, and consolidation through acquisition by the platform occurs slowly over time, creating industry shakeout-type dynamics. In this example, since $z_A < z_E$, the platform acquires any project it meets and so the steady state features only projects operated by the platform.

The evolution of project types affects the expected winner quality, shown in the

	Val.	Interp.	Source
ρ	0.03	HH discount rate	stnd.
β	0.6	labor share	stnd.
θ	1.26	pareto tail	Kondo, Lewis, and Stella (2021)
μ	0.04	merger mtg. rate	David (2020)
ι	0.03	qual. revelation rate	–
ϕ	2.6	flow operating cost	–
λ_E	0.03	entrant R&D	–
λ_P	0.15	platform R&D	–
χ	0	flow merger cost	–
η	0.02	new patent races	–

Table 2: Parameter values, illustrative example.

left panel of Figure 2. The dashed line shows expected quality in a counterfactual economy where the measure of firms is the same but the merger meeting rate is set to zero so all projects are operated by startups. This raises the shutdown threshold for bad projects and raises expected quality significantly as the patent race unfolds. The right panel of Figure 2, however, shows that because the aggregate arrival rate is high, few races last long enough to approach the industry steady state. Instead the vast majority of races conclude within 20 years.

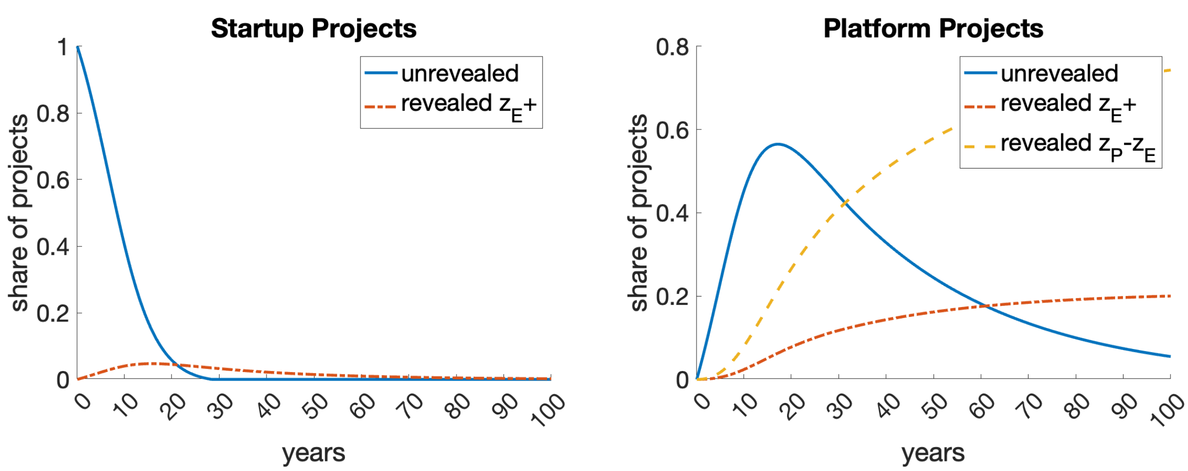

Figure 1: Patent race entry and acquisition dynamics.

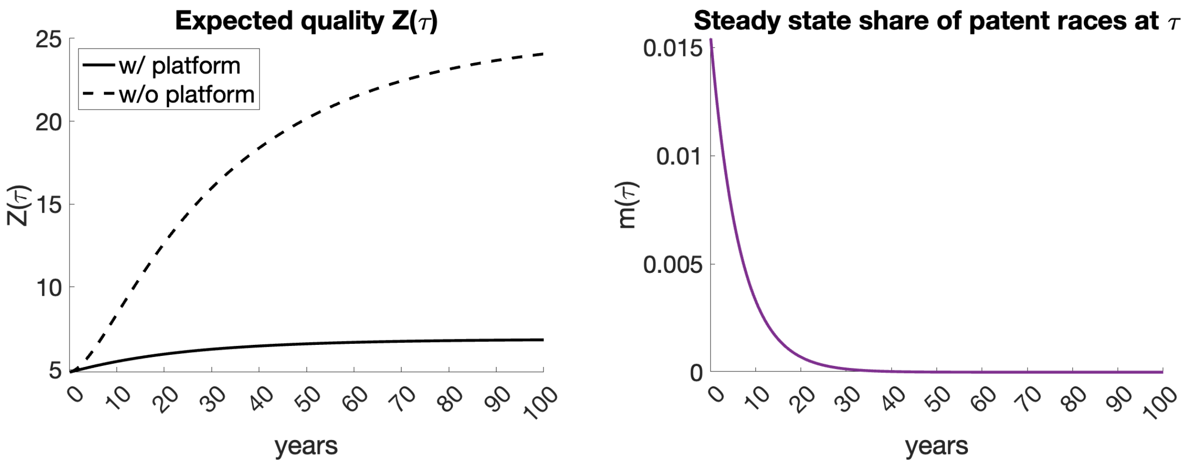

Figure 2: Steady state fraction of races at time τ and expected winner quality during the race.

6.2 Comparative Statics

This section studies the effects of the merger meeting rate μ and the acquirer's R&D arrival rate λ on the average product quality of incumbents z^*, the share of final output invested in creating new products and the steady state consumption share. We also plot the steady state share of intermediate goods produced by the platform. Note that these parameters have no effects on the growth rate because they do not appear in the free entry curve Equation 1. We consider changes of 30% in either direction to each parameter, holding the others fixed. Comparative statics for the other model parameters are plotted in Appendix B.

First consider the merger meeting rate, with results shown in Figure 3. A higher merger rate raises the platform's share of steady state varieties. It also means the platform meets more projects with unrevealed quality such that these projects are kept running when their quality turns out to be low. However, the higher fraction of projects operated by the platform means new product creation is more efficient, and the R&D investment share of total output falls. The overall effect on the consumption share of final output is therefore positive. We evaluate the welfare effects of these changes in the next section.

Turning to the parameter λ_P, which can capture technological or marking complementarities between targets and acquirers, we find similar results. A higher value of this parameter lowers the shutdown threshold for the platform so the effects on quality are weakly negative, though they reach a maximum where $z_P = \underline{z}$ so that the expected quality of revealed and unrevealed platform projects are the same. Similar to the merger meeting rate, greater complementarities raise the steady state platform share and the consumption share of final output.

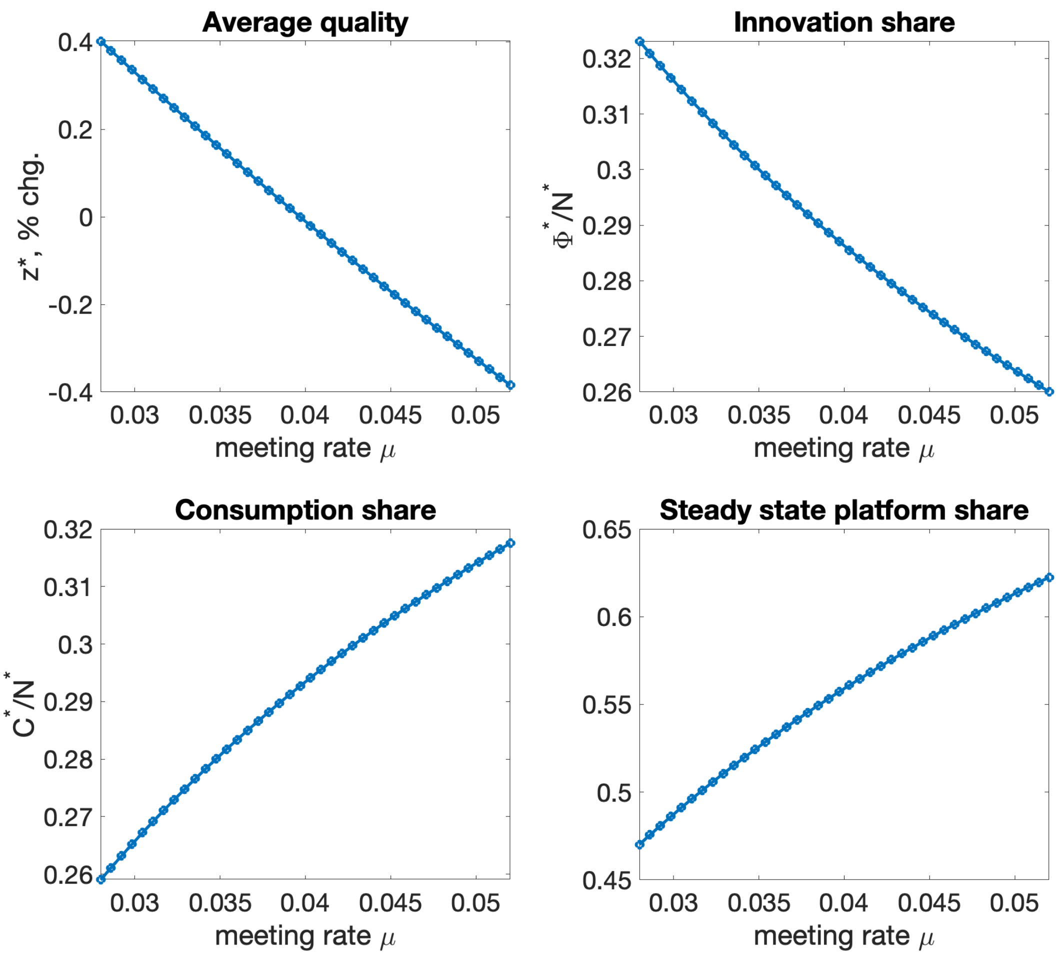

Figure 3: Comparative Statics: Merger Meeting Rate μ

6.3 Welfare Analysis

To the extent that policymakers can act directly on the merger meeting rate, we analyze the welfare effects of changes in this parameter in Table 3. The efficiency gains in new product creation brought on by a higher merger rate dominate the negative quality effects and raise consumer welfare relative to the baseline calibration. The gains are smaller over the transition because the economy starts with an initial condition for the number of varieties n^*_{old} that dampens the gains from this change.

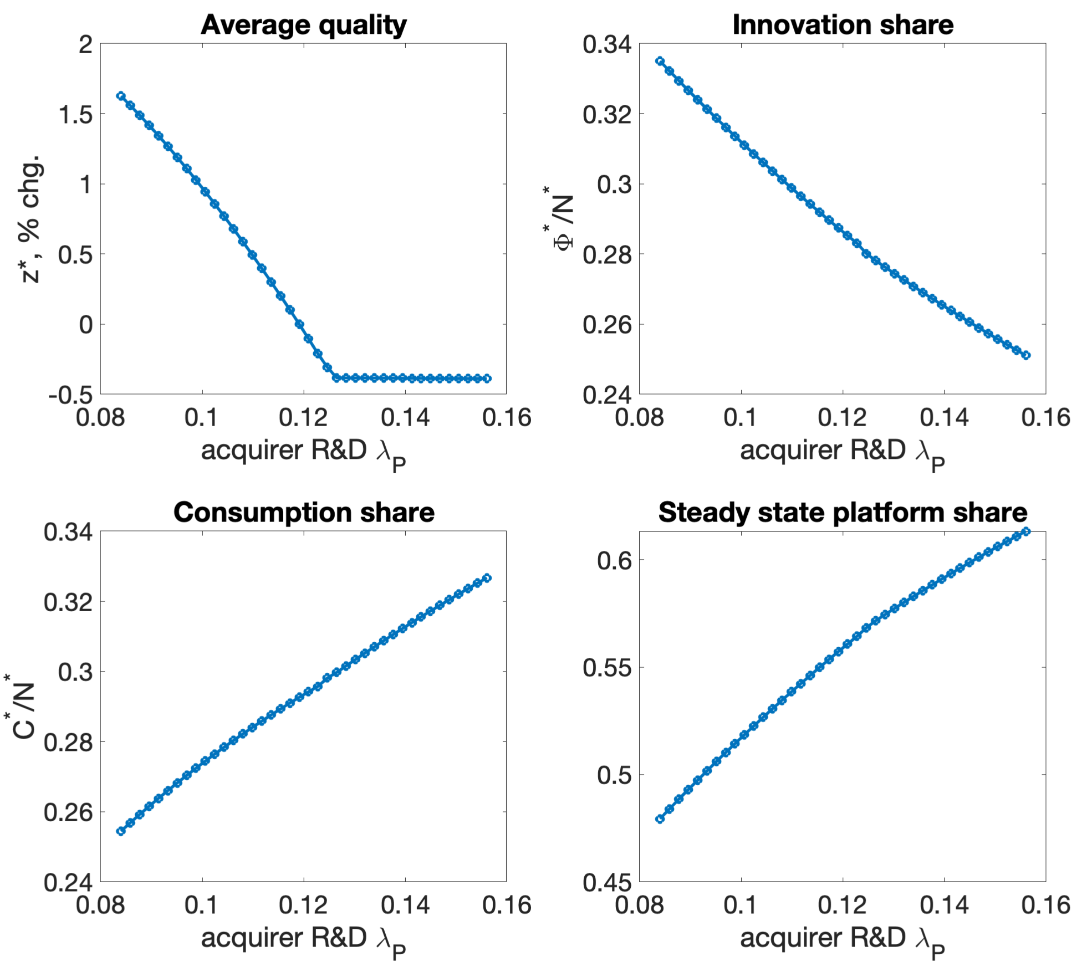

Figure 4: Comparative Statics: Acquirer R&D Arrival Rate λ_P

	$\mu = 0.028$	$\mu = 0.052$
	BGP (Base = 100)	
Quality z^*	100.4	99.6
Innovation Input ϕ^*	114	92
$\implies$ Consumption Share c^*/n^*	90	110
Number of Varieties n^*	98	103
Growth Rate g	100	100
	Welfare (CE)	
Steady State	88	114
Transition	92	109

Table 3: Welfare effects of $\pm 30\%$ changes to merger meeting rate μ relative to baseline rate of 4% annually. CE is consumption equivalent.

7 Conclusion

The model presented here offers a theoretical framework capturing many salient features of acquisitions' affects on growth, and of acquisitions by platform-based firms in particular. Many acquisitions, particularly by platform-based firms, are cross-industry, yet much of the literature so far has focused on acquisition of direct competitors. Understanding this other group of acquisitions is important in the context of a policy debate to increase scrutiny on, or even ban, acquisitions by platform firms.

The model highlights the role of mergers in bring new technologies to market faster and more efficiently. At the same time, we introduce heterogeneous project quality and show that acquisitions can have a negative effect on average product quality in the economy, which reduces welfare. This negative selection worsens as the technological advantage of acquirers in bringing new products to market grows.

In future versions we plan to explore some special aspects of platforms that have been highlighted in the competition policy literature through the lens of our model. These include the search and vetting capabilities that platforms use to search for targets who operate on the platform, the technological complementarities and zero marginal cost scaling enjoyed by platforms, and bargaining power differences between traditional and platform acquirers. Using data on age at acquisition, measures of information revelation like pre-acquisition patents, net income, and profits, and the merger premium paid by platforms, we will quantitatively evaluate these channels.

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A Computational Appendix

A.1 Balanced Growth Path

We discretize the continuous time model in order to find the balanced growth path pair $\{g, \Lambda^*\}$. All other variables can be solved given this pair. The solution algorithm proceeds as follows:

1. Obtain bounds on the balanced growth rate g. The minimum possible growth rate (with entry) is the one that sets the value of an unrevealed entrant to zero:
$$\frac{\theta}{\theta-1}\frac{\lambda_E \beta L \underline{z}}{\rho+g_{min}} = \phi.$$
The maximum possible growth rate is the one that sets the value of entry to zero with an aggregate arrival rate $\Lambda^* = 0$:
$$0 = \frac{\theta}{\theta-1}\frac{\lambda_E \beta \underline{z} L}{\rho+g_{max}} - \phi + \frac{\iota}{\rho+g_{max}+\lambda_E} z_E{}^{-\theta}\left(\frac{\theta}{\theta-1}\frac{\lambda_E \beta z_E L}{\rho+g_{max}} - \phi\right).$$
2. Guess a growth rate g between these bounds and use equation 1 to find Λ^*.
3. Simulate the flow equations in section 4.4.3 forward for many periods (T = 1000) to obtain the full path $\Lambda(\tau)$.
4. Use Equation 8, which we call the flow balance curve, to find the implied growth rate given $\Lambda(\tau)$.
5. Update the guess of g given the implied growth rate until the guess and the implied growth rate converge.

A.2 Transition Dynamics

The method for solving the transition dynamics of the model away from the BGP follows a similar approach, except that now we conjecture a full time path for the growth rate $g(t)$.

1. Guess $g(t)$. Through the Euler equation this implies a path for the interest rate $r(t) = \rho + g(t)$. We look for the function $R(t)$ that solves $r(t)R(t) = 1 + R'(t)$:
$$R(t) = \int_t^\infty e^{-\int_t^s r(t)dt} ds.$$
This implies time-varying thresholds for project shutdown:
$$z_E(t) = \frac{\phi}{\lambda_E R(t)\beta L}, \quad z_P(t) = \frac{\phi}{\lambda_P R(t)\beta L}.$$

The value of being a monopolist is also time-varying:

$$V_m(z,t) = \beta LR(t)z.$$

We have a time-varying path of arrival rates with the patent rate $\Lambda(\tau, t)$ so that the free entry curve becomes:

$$0 \geq \frac{\theta}{\theta-1}\lambda_E \beta LR(t) - \phi + \frac{\iota}{\rho + g(t) + \Lambda(\tau,t) + \lambda_E}(z_E(t))^{-\theta}\frac{1}{\theta-1}\phi$$

2. Obtain the time varying mass of entrants $\epsilon(0,t)$ from the modified free entry curve which holds with equality for $\Lambda^*(t)$ and then simulate forward the flow equations in section 4.4.3 to obtain $E_A(\tau,t)$, $E_U(\tau,t)$, $\psi(\tau,t)$, $P_A(\tau,t)$, $PU(\tau,t)$ and $\Lambda(\tau,t)$.

3. Given $\Lambda(\tau,t)$ find the implied path for the growth rate from the modified flow balance curve:

$$g(t) = \eta \int_0^\infty e^{\int_0^\tau -\Lambda(s,t-\tau+s)-g(t-\tau+s)ds}\Lambda(\tau,t)dt.$$

4. Update the guess for $g(t)$ until the conjectured and implied growth rate paths converge.

B Additional Comparative Statics

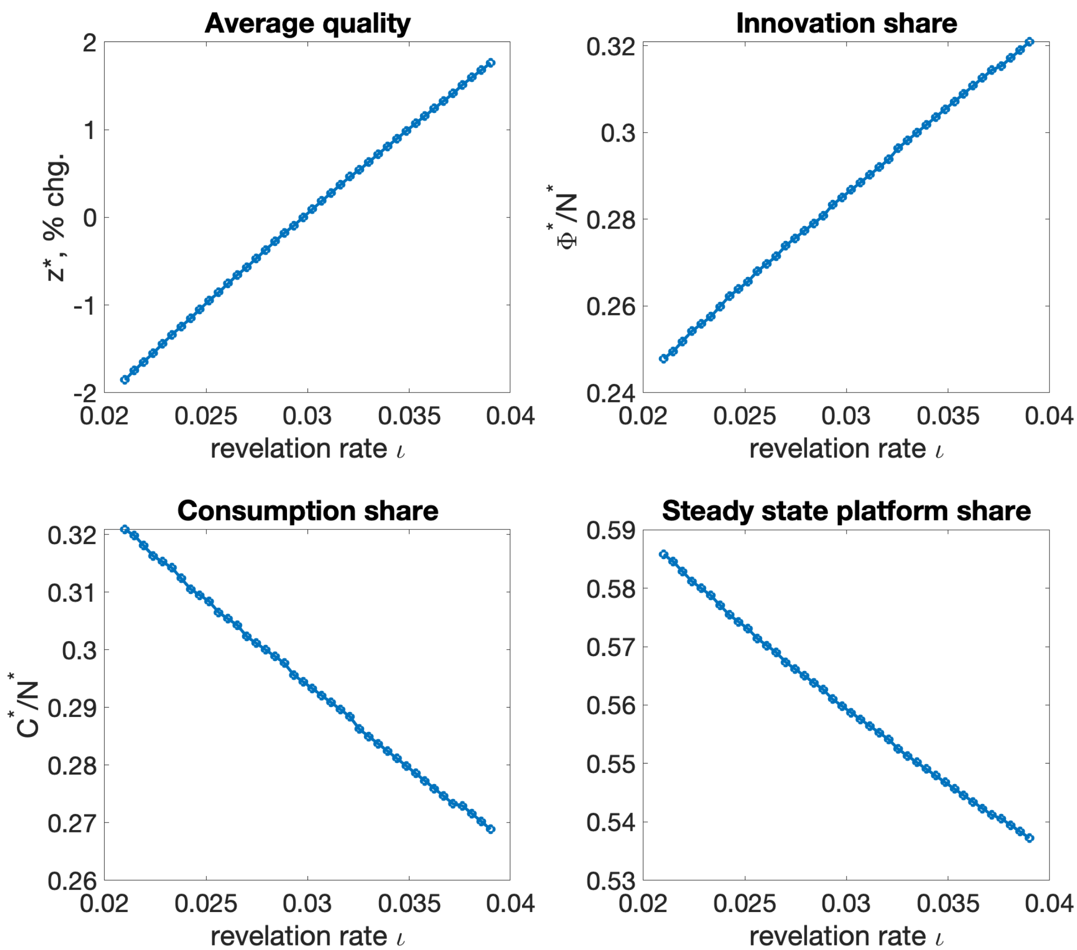

Figure 5: Comparative Statics: Project Quality Revelation Rate ι

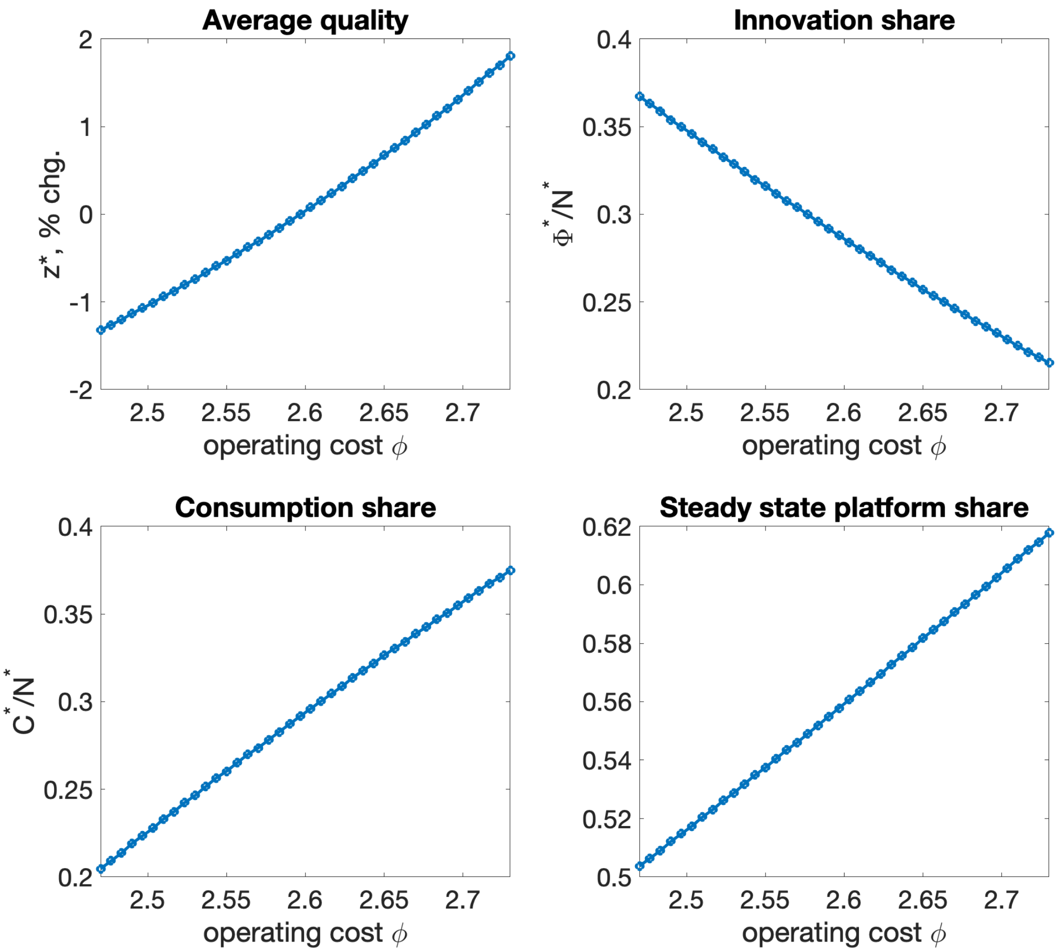

Figure 6: Comparative Statics: Project Operating Cost ϕ

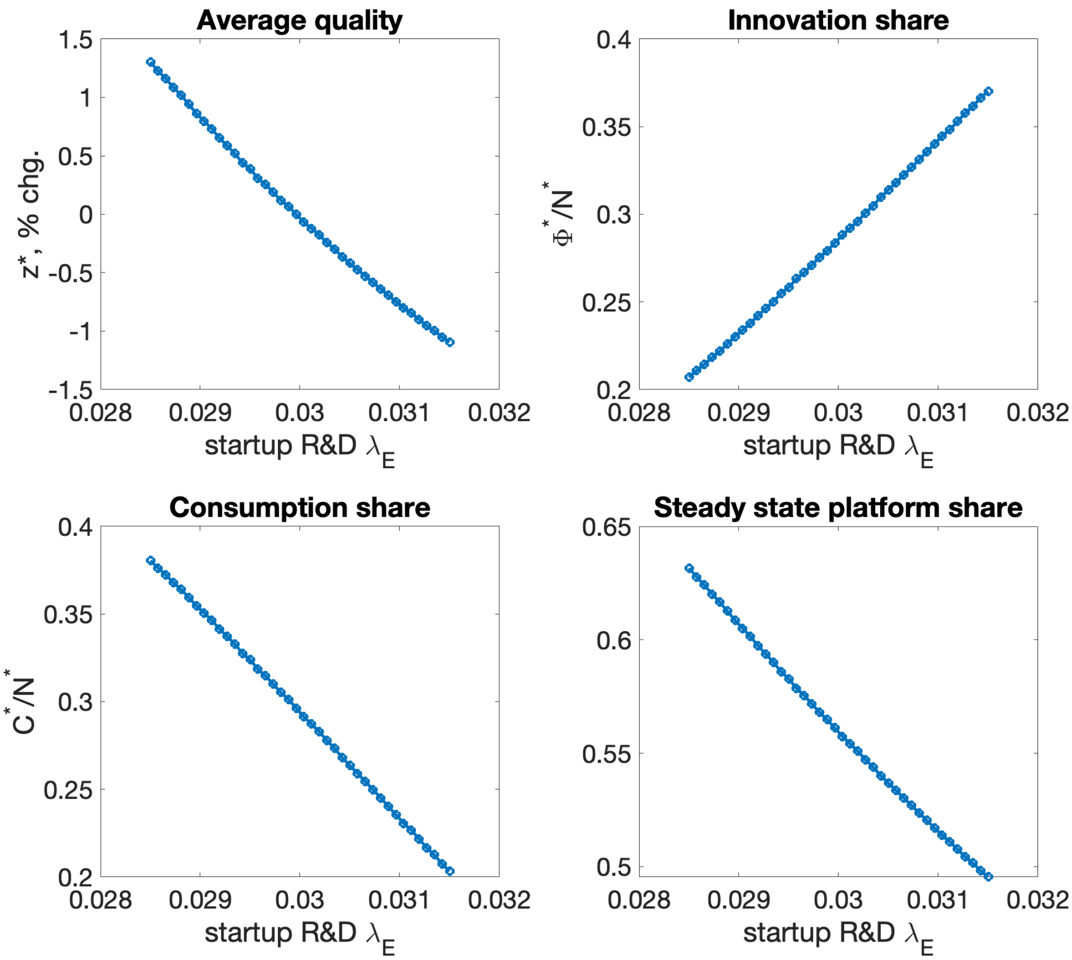

Figure 7: Comparative Statics: Startup R&D Funding λ_E

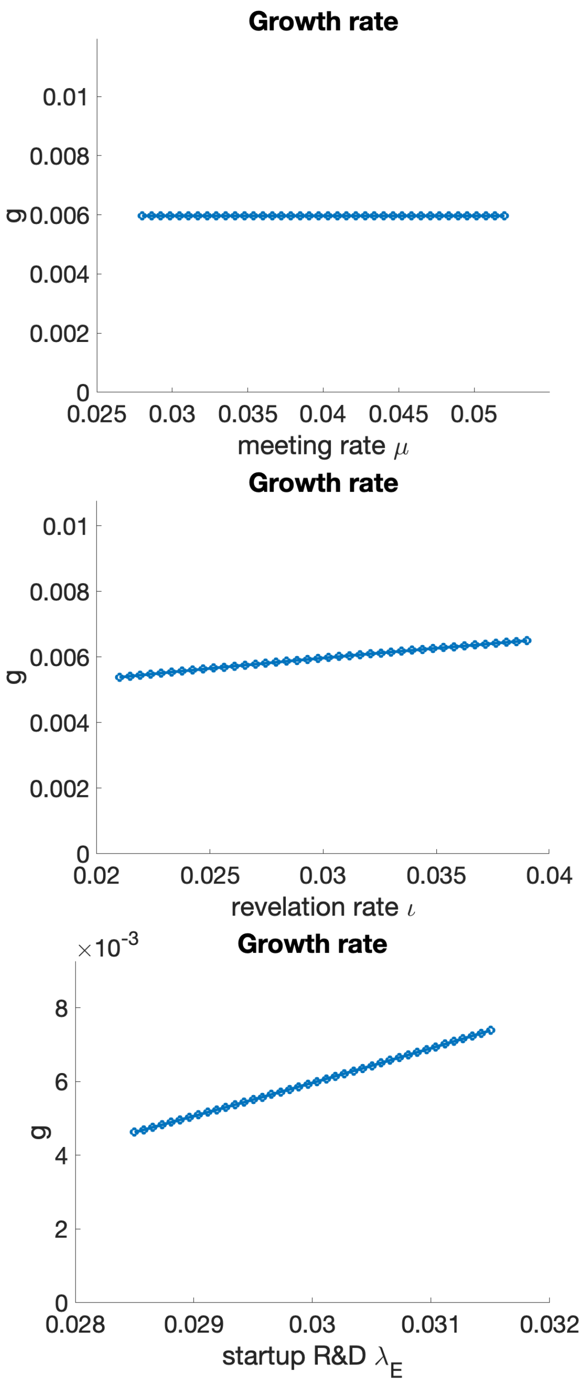

Figure 8: Comparative statics: growth rate effects of various model parameters.