The Effects of Startup Acquisitions on Innovation and Economic Growth*

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* The views expressed herein are the authors' and may not represent those of Banco de España or the Eurosystem.

Motivation

- Startups are an important driver of US productivity growth.
- However, large incumbent firms routinely acquire them.
- Regulators are increasingly skeptical:
  - Traditional concern is on market power and barriers to entry.
  - *But...* Increasing concern about the effects of startup acquisitions on innovation.

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FTC's Press Release contesting Facebook's acquisitions of Instagram and Whatsapp (Dec. 2020)

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Potential Effects of Acquisitions on Economic Growth

- **Positive effects:**

  1. Acquisitions may stimulate startup creation ("entry-for-buyout" effect):
     - Startups may expect to be bought up $\longrightarrow$ Acquisition as an attractive "exit strategy"
  2. Acquisitions may allow the transfer of ideas to more efficient users:
     - Incumbents may be better at implementing innovations (economies of scale, network effects...)

- **Negative effects:**

  1. "Killer acquisitions" [Cunningham, Ederer and Ma (2021)]:
     - Incumbents may buy startup to avoid being displaced, and then shelve startup's idea
     - Implementation would displace pre-existing incumbent profits (Arrow replacement effect)
  2. Acquisitions may lower incumbent's own innovation:
     - Incumbents might have no further incentive to innovate if acquisitions protect them against entry

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Roadmap

1. Model: Heterogeneous Firms + Schumpeterian Growth + Acquisitions:

- Features all positive and negative effects of acquisitions on growth mentioned in the previous slide.
- Shows that effects of acquisitions on growth can be decomposed into 3 key margins:
  - (i) the startup rate
  - (ii) the % implemented startup ideas
  - (iii) the own innovation rate of incumbents

2. Empirics:

- Micro-data combining (i) acquisitions data, (ii) patent data, (iii) balance-sheet data (Compustat).
- Provide calibration targets and study causal effect of startup acquisitions on startup's patents.

3. Calibration and Quantitative Analysis:

- In our baseline calibration, acquisitions are detrimental to growth (though only barely).
- Prohibiting acquisitions $\Rightarrow$ **growth** $\uparrow$ 0.03ppt (or 1.6%) and **CE welfare** $\uparrow$ by 1.8%, coming from:
  - (−) Startup rate $\downarrow$ 14.9%
  - (+) More startup ideas get implemented ($\uparrow$ 8.4%)
  - (+) Incumbents innovate more on their own ($\uparrow$ 5.3%)

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Related Literature

1. **Cross-sectional evidence on the effects of M&As on innovation**:
   Phillips and Zhdanov (2013), Bena and Li (2014), Seru (2014), Blonigen and Pierce (2016), Kim (2020), Cunningham, Ederer and Ma (2021).

2. **Macroeconomic effects of M&As**:
   (i) *Investment and the allocation of capital:*
   Jovanovic and Rousseau (2002), Rhodes-Kropf and Robinson (2008), Dimopoulos and Sacchetto (2017), David (2020).

   (ii) *Endogenous growth models:*
   Akcigit, Celik and Greenwood (2016), Lentz and Mortensen (2016), Cavenaile, Celik and Tian (2020), Weiss (2022).

3. **Acquisitions and innovation in IO models**:
   Cabral and Polak (2012), Federico, Langus and Valletti (2017), Cabral (2018), Bourreau, Jullien and Lefouili (2018), Bryan and Hovenkamp (2020), Callander and Matouschek (2020), Fumagalli, Motta and Tarantino (2020), Kamepalli, Rajan and Zingales (2020), Letina, Schmutzler and Seibel (2020), Denicolò and Polo (2021).

Contribution: Combine IO insights into *GE framework* and quantify *dynamic macro* consequences.

Model

Environment

- **Preferences:**

$$\max \int_0^{+\infty} e^{-\rho t} \ln(C_t)\, \mathrm{d}t$$

- **Final good:**

$$Y_t = \exp\left(\int_0^1 \omega_{jt} \ln\left(\frac{y_{jt}}{\omega_{jt}}\right) \mathrm{d}j\right), \qquad \text{with} \int_0^1 \omega_{jt}\, \mathrm{d}j = 1$$

  - Product's spending share: $\omega_{jt} \in \{\omega_L, \omega_H\} \sim$ Markov process.

- **Technology:**

$$y_{jt} = a_{jt} l_{jt}$$

  - Bertrand game $\rightarrow$ Duopoly between *incumbent* (highest a_{jt}) and *follower* (previous incumbent).
  - To increase a_{jt} $\rightarrow$ Research (creation of new ideas) and Development (implemention).

R&D: Incumbents

R&D is split into two stages:

- **Research:** To obtain Poisson arrival rate z of ideas, pay a cost:

$$R_{jt} = \xi_I z^{\psi} Y_t, \qquad \text{where } \xi_I > 0,\ \psi > 1$$

- **Development:** To develop new idea with probability i_I, pay a cost:

$$D_{jt} = \kappa_I {i_I}^{\psi} Y_t, \qquad \text{where } \kappa_I > 0$$

  - If idea is not developed immediately, it is lost forever.
  - If idea is developed it becomes an innovation $\rightarrow$ Increases a_{jt} to λa_{jt}, where $\lambda > 1$.

Startups

- **Startup creation:**
  - A startup can be created at a fixed cost $\xi_S Y_t$, where $\xi_S > 0$.
  - Startup generates Poisson arrival rate of ideas equal to 1.
- **Development:**
  - A startup's idea applies to a randomly drawn product $j \in [0, 1]$.
  - To develop idea with probability i_S, startup pays:

$$D_{jt}^S = \kappa_S {i_S}^{\psi} Y_t, \quad \text{where } \kappa_S > 0$$

  - Startup innovations:
    - Increase a_{jt} to $\lambda^{n_S} a_{jt}$, where $n_S = 1 + N$ and $N \sim \text{Poisson}(\gamma)$.
    - N is revealed *after* investment into development.
  - When a startup implements its idea, it displaces the old incumbent:
    - Startup becomes new producer, old incumbent becomes new "follower".

Acquisitions

- Incumbents make acquisition offers to startups if they "meet" them.
- **Acquisition market:**
  - To generate a meeting with a startup with probability s, incumbent pays search cost:

$$S_{jt} = \chi s^{\varphi} Y_t, \quad \text{where } \chi > 0, \ \varphi > 1$$

  - Conditional on a meeting:
    - Nash-bargaining over an acquisition price, with incumbent bargaining weight $\alpha \in (0, 1)$.
    - Startup agrees to transfer idea to incumbent and exit forever.
- **After an acquisition:**
  - Incumbent chooses development probability i_A for acquired startup's idea.
  - Uses its own development technology:

$$D_{jt} = \kappa_I {i_A}^{\psi} Y_t$$

Life-Cycle of a Startup's Idea (overview)

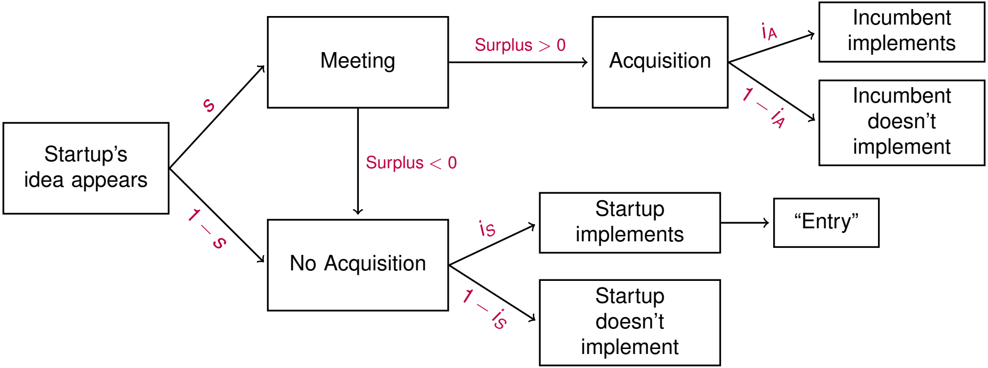

Figure: Timing of events for a startup's idea within a period $(t, t+dt)$.

Static Equilibrium Conditions

- Bertrand competition: Incumbent sets low enough markup to drive out follower (s.t. $p_{jt} = MC^F_{jt}$):

$$\mu_{jt} \equiv \frac{p_{jt}}{MC_{jt}} = \frac{MC^F_{jt}}{MC_{jt}} = \frac{w_t/a^F_{jt}}{w_t/a_{jt}} = \lambda^{n_{jt}}, \qquad \text{where } n_{jt} \in \{1, 2, 3, \ldots\} \text{ is the technology gap}$$

- Static profits:

$$\pi_t(\omega_{jt}, n_{jt}) = \omega_{jt}\left(1 - \lambda^{-n_{jt}}\right) Y_t,$$

  - Markups (μ) and profits (π) are *increasing* in n.
  - Profits are *concave* in n $\rightarrow$ Incentives for own innovation are highest at low n's.

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HJB Equations I

- **Value of an incumbent:**

$$rV_t(\omega, n) = \max_{z,s} \Bigg\{ \underbrace{\pi_t(\omega, n)}_{\text{Profits}} - \underbrace{\xi_I z^{\psi} Y_t}_{\text{Research cost}} - \underbrace{\chi s^{\varphi} Y_t}_{\text{Search effort}}$$

$$+ \underbrace{z \max_{i_I} \Big[i_I \Big(V_t(\omega, n+1) - V_t(\omega, n) \Big) - \kappa_I i_I^{\psi} Y_t \Big]}_{\text{Own innovation}}$$

$$+ \underbrace{x \Big[\text{[illegible]} \Big]}_{\text{Startup appears}} \Bigg\}$$

$$+ \underbrace{\sum_{\omega' \in \Omega} \tau_{\omega,\omega'} \Big[V_t(\omega', n) - V_t(\omega, n) \Big]}_{\text{Quality shock}} + \underbrace{\dot{V}_t(\omega, n)}_{\text{Drift}}$$

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HJB Equations II

- **Values if no meeting occurs** $\rightarrow$ Outside options:

$$\text{Startup}: \quad V^{\text{NoMeet}}_{S,t}(\omega) = \max_{i_S}\left\{ \underbrace{i_S\, \mathbb{E}_{n_S}\Big[V_t(\omega, n_S)\Big]}_{\text{Entry}} - \kappa_S {i_S}^{\psi} Y_t \right\}$$

$$\text{Incumbent}: \quad V^{\text{NoMeet}}_{t}(\omega, n) = \underbrace{\Big[1 - i_{S,t}(\omega, n)\Big] V_t(\omega, n)}_{\text{No displacement}}$$

- **Value if acquisition occurs** $\rightarrow$ Joint surplus:

$$\Sigma_t(\omega, n) = \max_{i_A}\left\{ V_t(\omega, n) + \underbrace{i_A \left(\mathbb{E}_{n_S}\Big[V_t(\omega, n + n_S)\Big] - V_t(\omega, n)\right)}_{\text{Implement startup's idea}} - \kappa_I {i_A}^{\psi} Y_t \right\}$$

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HJB Equations III

- Surplus split via Nash bargaining:

$$\text{Startup}: \quad V_{S,t}^{\text{Meet}}(\omega, n) = V_{S,t}^{\text{NoMeet}}(\omega) + (1-\alpha) \max\left\{0, \Sigma_t(\omega, n)\right\}$$

$$\text{Incumbent}: \quad V_{t}^{\text{Meet}}(\omega, n) = V_{t}^{\text{NoMeet}}(\omega, n) + \alpha \max\left\{0, \Sigma_t(\omega, n)\right\}$$

- Startup rate x determined from free-entry condition:

$$\underbrace{\xi_S Y_t}_{\text{Creation cost}} = \mathbb{E}_{\omega,n}\left[\underbrace{s_t(\omega, n) V_{S,t}^{\text{Meet}}(\omega, n) + \left(1 - s_t(\omega, n)\right) V_{S,t}^{\text{NoMeet}}(\omega)}_{\text{Value of a startup}}\right]$$

- We solve for a Balanced Growth Path (BGP) in which: ▸ Details

  1. The joint distribution of spending shares and technology gaps, $m(\omega, n)$, is *time-invariant*.
  2. Aggregates grow at constant rate $g = r - \rho > 0$.
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Decomposition of the Growth Rate

- Growth rate in BGP:

$$g = \ln(\lambda) \cdot \underbrace{\left((1+\gamma) \cdot \underbrace{x}_{\substack{\text{Startup}\\ \text{rate}}} \cdot \underbrace{\mathcal{P}}_{\substack{\text{Percentage of imple-}\\ \text{mented startup ideas}\\ \text{(sales-wtd avg)}}} + \underbrace{\mathcal{I}}_{\substack{\text{Incumbents'}\\ \text{own innovation}\\ \text{(sales-wtd avg)}}} \right)}_{\text{Average innovation rate}},$$

- Change in growth between two BGPs, "*A*" and "*B*": Derivation

$$\frac{g^B}{g^A} = \vartheta^A \frac{x^B}{x^A} \frac{\mathcal{P}^B}{\mathcal{P}^A} + \left(1 - \vartheta^A\right) \frac{\mathcal{I}^B}{\mathcal{I}^A},$$

where $\vartheta^A \equiv$ Share of growth accounted for by startup ideas in BGP "*A*".

- In turn, effects on each of the three relevant margins $(\mathcal{I}, x, \mathcal{P})$ depend on:

1. **Level effects:** Arrow replacement effect vis-a-vis implementation cost differences (*next up*).
2. **Composition effects:** changes in the distribution of firms (*calibration*).

Optimal Implementation Policies

- Optimal implementation probabilities (i_S, i_I, i_A):

Who implements	*Whose idea*	*Marginal cost*		*Marginal benefit*
Startup	Startup	$\kappa_S \psi (i_S)^{\psi-1}$	$=$	$\mathbb{E}_{n_S}[v(\omega, n_S)]$
Incumbent	Startup	$\kappa_I \psi (i_A)^{\psi-1}$	$=$	$\mathbb{E}_{n_S}[v(\omega, n+n_S)] - v(\omega, n)$
Incumbent	Incumbent	$\kappa_I \psi (i_I)^{\psi-1}$	$=$	$v(\omega, n+1) - v(\omega, n)$

- **Key margins:**

  1. Relative implementation costs (*favors incumbents* if $\kappa_I < \kappa_S$).
  2. Arrow replacement effect (*favors startups*).
     - Marginal gain is smaller for incumbents because innovation cannibalizes previous profits.

- **Two types of acquisition** $\rightarrow$ **"innovative"** (if $i_A > i_S$) or **"killer"** (if $i_A < i_S$).

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Who implements	*Whose idea*	*Marginal cost*		*Marginal benefit*
Startup	Startup	$\boldsymbol{\kappa_S} \psi (i_S)^{\psi - 1}$	$=$	$\mathbb{E}_{n_S}\left[v(\omega, n_S)\right]$
Incumbent	Startup	$\boldsymbol{\kappa_I} \psi (i_A)^{\psi - 1}$	$=$	$\mathbb{E}_{n_S}\left[v(\omega, n + n_S)\right] - v(\omega, n)$
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- **Key margins:**
  1. **Relative implementation costs** (*favors incumbents* if $\kappa_I < \kappa_S$).
  2. Arrow replacement effect (*favors startups*).
     - Marginal gain is smaller for incumbents because innovation cannibalizes previous profits.
- **Two types of acquisition** $\rightarrow$ **"innovative"** (if $i_A > i_S$) or **"killer"** (if $i_A < i_S$).

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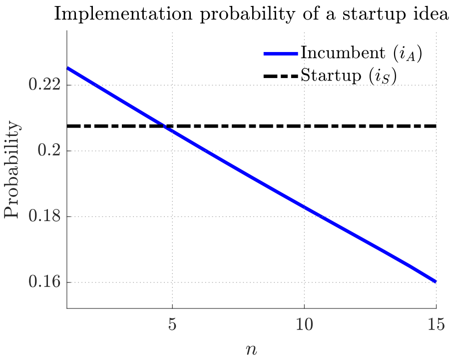

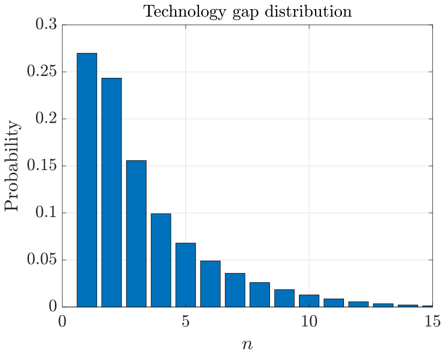

1. Implementation costs (*favors incumbents*).
   - $\kappa_I < \kappa_S$.
   - Force toward $i_A > i_S$ (*innovative acquisition*)
2. Arrow replacement effect (*favors startups*).
   - Dominates for high n's.
   - Force toward $i_A < i_S$ (*killer acquisition*)

- To discipline these margins, we turn to the data.

Empirics

Data

- **Data sources:** We merge data from three sources:
  1. **ThomsonONE M&A database:** M&As between US firms, 1981-2014.
  2. **NBER Patent Data project:** US patent data, 1976-2006.
  3. **Compustat:** Balance sheet and income statements, US publicly listed firms, since 1960s.
- **Caveat:** No age info on private firms $\rightarrow$ We define firm as "startup" if it is within 6 years of first patent.
  - *But...* Work in progress $\rightarrow$ New data (**SDC Platinum**) contains foundation date of acquisition targets.
- **Some stylized facts:** (for the calibration)
  1. Startup patents are, on average, of higher quality than patents of incumbents:
     - Startups account for 27% of patents, but 74% of all patent citations.
  2. Selection in the acquisition process:
     - **Acquirers:** Acquiring firms are 2.1 times larger (in sales) than the average firm.
     - **Targets:** Acquired startup patents receive 4 times more citations than the average startup patent.

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Effects of Acquisitions on Startup's Idea

- In the model, an important dimension of effect of acquisitions on g is effect on implementation probabilities.
- **Empirical question:** Are startup ideas more or less likely to be implemented after startup is acquired?
  - We proxy idea implementation with change in citations received after acquisition.
  - If citations $\uparrow$, evidence that incumbent builds on startup idea $\Rightarrow$ More likely implemented.
- **Empirical strategy:** Matching method (*nearest neighbor*) design:
  - For each patent from acquired startup (treated), select a group of patents from non-acquired startups (control group) that matches in application year, technology class, pre-acquisition citation trend, and various text-based patent characteristics. ▸ Match quality
  - Poisson regression specification:

$$\underbrace{NumCites_{ijt}}_{\substack{\#\text{ citations received} \\ \text{per patent-year}}} = \beta_1 \underbrace{D(Treatment)_i}_{=1,\text{ if } i \text{ is treated}} + \beta_2 \underbrace{D(Post)_{it}}_{=1,\ \forall t \text{ after acq.}} + \beta_3 \underbrace{D(Treatment)_i \cdot D(Post)_{it}}_{\text{Interaction term}} + \alpha_j + \alpha_t + u_{ijt}$$

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Results

Dependent variable: Number of citations received

	(1)	(2)	(3)	(4)
D(Post)	0.405***	0.397***	0.439***	0.346***
	(0.028)	(0.019)	(0.030)	(0.019)
D(Treatment)	-0.016	-0.014	-0.013	-0.010
	(0.068)	(0.062)	(0.038)	(0.035)
D(Post)*D(Treatment)	0.228***	0.226***	0.222***	0.218***
	(0.051)	(0.050)	(0.044)	(0.041)
Observations	206,432	206,432	206,352	206,352
Matched Pair FE			✓	✓
Year FE		✓		✓

Notes: We use a Poisson estimator. All specifications have 10 control patents for each treated patent, and a 7-year pre-post acquisition window. Standard errors are clustered at the target firm level. Significance: *=10%; **=5%; ***=1%.

- Relative to control, when a startup patent is acquired its number of forward citations increases by 22%.
- **Robustness:** Across various different specifications, acquisitions increase citations. Robustness

Heterogeneous Effects

- The boost to citations is lower if:
  1. The acquirer has a high market share (in line with baseline model).
  2. The acquirer and the startup belong to the same industry (in line with multi-product extension).

Dependent variable: Number of citations received

	Market Share		*Same SIC3*		*Same SIC3/NAICS4*	
	Above	Below	Same	Different	Same	Different
D(Post)	0.371***	0.334***	0.361***	0.332***	0.399***	0.325***
	(0.022)	(0.020)	(0.023)	(0.021)	(0.022)	(0.022)
D(Treatment)	0.004	0.004	0.030	-0.043	0.004	-0.031
	(0.052)	(0.044)	(0.045)	(0.049)	(0.050)	(0.046)
D(Post) * D(Treatment)	0.158***	0.249***	0.132**	0.288***	0.158***	0.264***
	(0.059)	(0.048)	(0.054)	(0.051)	(0.055)	(0.051)
Observations	88,187	92,480	83,500	122,817	67,359	130,598
Matched Pair FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: We use a Poisson estimator. Columns (1)-(2) split the sample by the median of acquirer market share defined at the SIC3-year level, where column (1) keeps the observations above the median in market share and column (2) the ones below. Columns (3)-(4) split the sample based on whether both acquirer and target have the same primary SIC 3-digit industry code. Finally, columns (5)-(6) replicate the exercise with a sample split requiring both firms to have the same SIC 3-digit industry code (until 1997) and the same NAICS 4-digit industry code (since 1997). Standard errors are clustered at the target firm level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Calibration

Calibration Strategy

- **Externally identified:**
  1. Standard/literature $\rightarrow \rho = 0.02$; $\psi = 2$.
  2. Spending shares $\rightarrow \omega_H/\omega_L = 16$ with $\tau_{HL} = 0.1$, to match sales share of 20% largest firms (Compustat).
  3. Bargaining parameter $\rightarrow \alpha = 0.5$, from David (2020).
  4. Productivity advantage of startup ideas $\rightarrow \gamma = 0.415$, from citation advantage of startup patents.

- **Internally identified:**
  1. Research cost parameters (ξ_I, ξ_S):
     - $\rightarrow$ Match exit rate (5.8%), from BDS, and contribution of entrants to growth (25.7%), from Akcigit & Kerr (2018).
  2. Relative implementation cost, κ_I/κ_S:
     - $\rightarrow$ Match average effect of acquisitions on implementation probability, from our regressions.
     - $\rightarrow$ Note κ level is not identified, results are invariant to average implementation probability of startups.
  3. Search cost parameters (χ, φ):
     - $\rightarrow$ Match share of startups that get acquired (4.0%), from Guzman and Stern (2020).
     - $\rightarrow$ Match relative size of acquirers (2.10), from our data.

Calibration

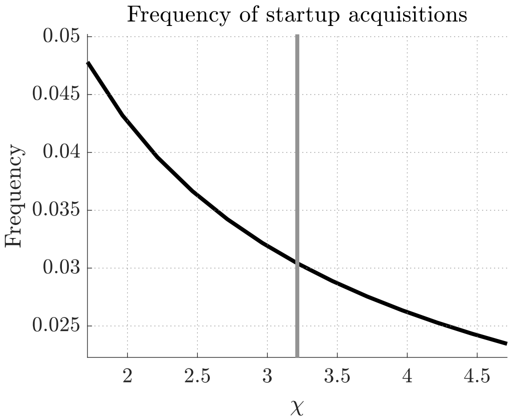
Computing Moments | Global Identification Results | Pictures: Value and Policy Functions

Parameter		**Value**	**Target** [Source]	**Model**	**Data**
Innovation step size	λ	1.030	Growth rate [Jones, 2016]	2.0%	2.0%
Startup creation cost	ξ_S	0.038	Exit rate [US Census' BDS]	7.3%	7.3%
Research cost (incumbent)	ξ_I	0.004	Growth contribution of entrants [Akcigit-Kerr, 2018]	25.7%	25.7%
Implementation cost (startup)	κ_S	2.447	Implementation prob. startup idea (by startup)	10.0%	10.0%
Implementation cost (inc.)	κ_I	1.391	Effect of acq. on implementation prob. [Regressions]	0.037	0.037
Search cost shifter	χ	3.214	Share of startups acquired [Guzman-Stern]	4.0%	4.0%
Search cost curvature	φ	2.725	Relative size (sales) of acquiring firms [Our data]	2.10	2.10
Discount rate	ρ	0.02	4% annual interest rate		
Relative spending share	ω_H/ω_L	16	Sales share of top 20% of firms [Our data]		
ω_H-to-ω_L transition rate	τ_{HL}	0.10	Yearly % of firms that transition out of top 20% sales share [Our data]		
R&D cost curvature	ψ	2	R&D elasticity [Akcigit and Kerr, 2018]		
Bargaining weight	α	0.50	David (2020)		
Advantage startup ideas	γ	0.415	Elasticity of value of patent [Kogan et al. (2017) and Our data]		

The Effects of Acquisitions on Innovation and Economic Growth

Effects of Startup Acquisitions on Growth

- Counterfactual exercise (comparing BGPs):
  - Vary χ (cost shifter in incumbents' search effort).
  - Plot resulting variation in frequency of acquisitions against other aggregates.



Note: Frequency of acquisitions is computed as *[startup rate]* $\times$ *[% startups acquired]*.

Effects of Startup Acquisitions on Growth

$$\Delta g = 0.28 \left(\Delta \text{ Startup rate}\right)\left(\Delta \text{ \% implemented startup ideas}\right) + 0.72 \left(\Delta \text{ Incumbents' own innov.}\right)$$

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   - Acquisitions allow startups to capture more than their outside option of independent entry.
2. ...but also *decreases* the % of implemented startup ideas and incumbents' own innovation ($g\downarrow$):
   - (a) Level effect:
   - (b) Composition effect:

→ Net effect is a priori ambiguous! In our calibration, negative forces slightly dominate, and $g\downarrow$

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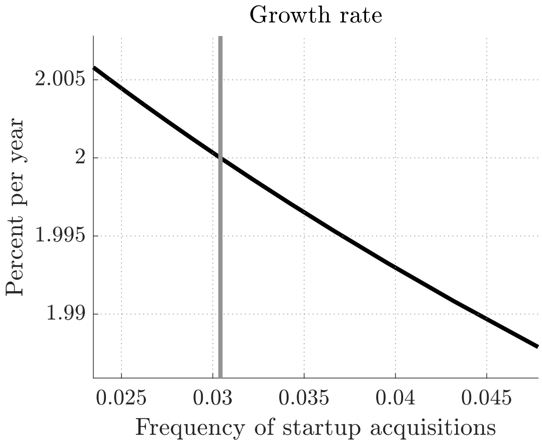

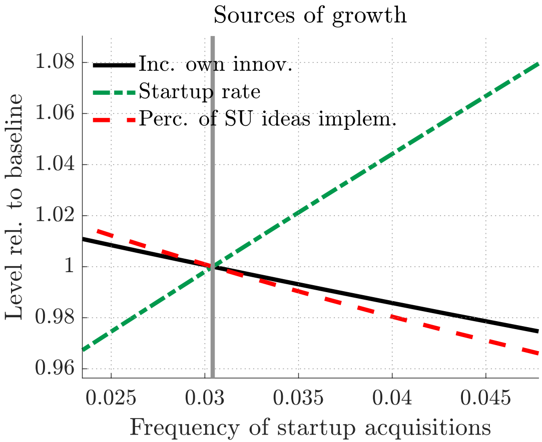

Acquisition Ban

- Banning all acquisitions **increases growth by 1.6%** and **welfare by 1.8%**. Partial Bans

Outcome	Baseline	Acq. Ban	% Change
Growth rate	2.00%	2.03%	**+1.4%**
Startup rate	0.760	0.647	−14.9%
% of implemented startup ideas	18.1%	19.6%	+8.4%
Incumbent own inn. rate	0.494	0.519	+5.3%
Entry rate	7.3%	7.2%	−1.6%
Aggregate markup	13.1%	13.1%	−0.4%
CE Welfare Details			**+1.8%**

- Ban still desirable when some acq. are non-competing (extended model with multiproduct firms). Go

- *But...* Acquisitions **not always** lower growth! Acquisitions can increase growth if...
  - ... incumbents sufficiently better at implementing (e.g. $\xi_I = \kappa_S = +\infty \Rightarrow$ no growth w/o acq's!). Go
  - ... entrants contribute more to overall growth. Go
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Conclusion

- GE growth model in which acquisitions have various positive and negative effects.
  - (+) May allow transferring ideas to more efficient users.
  - (+) May stimulate startup creation.
  - (–) May lower implementation efforts and lead to killer acquisitions.
- Key results:
  1. Acquisitions create an economy with high startup activity but less idea implementation.
  2. *In net terms* $\rightarrow$ Acquisitions are detrimental for growth (banning them is a good idea).
- Future research:
  1. Explore industry-level heterogeneity in the data, calibrate to model.
  2. Empirically identify the effect of acquisitions on researchers.

Thank you!

Appendix

Appendix: BGP Equilibrium Conditions (1/2)

Back to Equilibrium

- We guess-and-verify $V_t(\omega, n) = v(\omega, n) Y_t$. Define $\sigma(\omega, n) \equiv \max\left(0, \Sigma_t(\omega, n)\right) / Y_t$. Then,

$$\rho v(\omega, n) = \max_{z,s} \Bigg\{ \omega \left(1 - \frac{1}{\mu(n)}\right) - \xi_I z^{\psi} - \chi s^{\varphi} + z \max_{i} \left[i \Big(v(\omega, n+1) - v(\omega, n) \Big) - \kappa_I i^{\psi} \right] + x \Big[s \alpha \sigma(\omega, n) - i_S(\omega) v(\omega, n) \Big] \Bigg\} + \sum_{\omega'} \tau_{\omega,\omega'} \Big[v(\omega', n) - v(\omega, n) \Big]$$

- Optimal innovation and search intensity (incumbents):

$$s(\omega, n) = \left[\frac{x \alpha \sigma(\omega, n)}{\chi \varphi} \right]^{\frac{1}{\varphi - 1}}$$

$$z(\omega, n) = \left[\frac{i_I(\omega, n) \Big(v(\omega, n+1) - v(\omega, n) \Big) - \kappa_I \big(i_I(\omega, n) \big)^{\psi}}{\xi_I \psi} \right]^{\frac{1}{\psi - 1}}$$

Appendix: BGP Equilibrium Conditions (2/2)

Back to Equilibrium

- Optimal implementation choices:

$$
\begin{aligned}
\textit{Startup}: \quad & \kappa_S \psi \left(i_S\right)^{\psi-1} &= \quad & \mathbb{E}_{n_S}\left[v(\omega, n_S)\right] \\
\textit{Incumbent, own idea}: \quad & \kappa_I \psi \left(i_I\right)^{\psi-1} &= \quad & v(\omega, n+1) - v(\omega, n) \\
\textit{Incumbent, startup's idea}: \quad & \kappa_I \psi \left(i_A\right)^{\psi-1} &= \quad & \mathbb{E}_{n_S}\left[v(\omega, n+n_S)\right] - v(\omega, n)
\end{aligned}
$$

- The free-entry condition simplifies to

$$
\xi_S = \sum_{\omega\in\Omega} \sum_{n=1}^{+\infty} m(\omega)m(n)\left[v_S^{\text{NoMeet}}(\omega, n) + s(\omega, n)(1-\alpha)\sigma(\omega, n)\right].
$$

- Labor market clearing implies

$$
\frac{w_t L}{Y_t} = \sum_{\omega\in\Omega} \sum_{n=1}^{+\infty} m(\omega, n)\frac{\omega}{\mu(n)}.
$$

Appendix: Growth Decomposition Derivation

Back to Decomposition

- Growth rate in BGP:

$$g = \ln(\lambda)\Big(\,(1+\gamma)\,x\mathcal{P} + \mathcal{I}\Big),$$

where

$$\mathcal{I} \equiv \sum_{\omega\in\Omega}\sum_{n=1}^{+\infty}\omega m(\omega,n)z(\omega,n)i_I(\omega,n)$$

$$\mathcal{P} \equiv \sum_{\omega\in\Omega}\sum_{n=1}^{+\infty}\omega m(\omega,n)\Big(s(\omega,n)i_A(\omega,n) + \big(1-s(\omega,n)\big)\,i_S(\omega,n)\Big)$$

- Change in growth can be split into **3 components** ($*$ = Baseline BGP):

$$\frac{g}{g^*} = \underbrace{\frac{\ln(\lambda)\,(1+\gamma)\,x^*\mathcal{P}^*}{g^*}}_{=\vartheta}\frac{x}{x^*}\frac{\mathcal{P}}{\mathcal{P}^*} + \underbrace{\frac{\ln(\lambda)\mathcal{I}^*}{g^*}}_{=1-\vartheta}\frac{\mathcal{I}}{\mathcal{I}^*},$$

Appendix: Treatment and Control Patents

Back to Empirics

	Treatment Patents		Control Patents		*t*-test
	Obs.	Mean (St.dev.)	Obs.	Mean (St.dev.)	*p*-value
New Word Combination	2,519	140.81 (415.44)	25,135	131.86 (683.06)	0.52
New Bigrams	2,519	3.15 (4.73)	25,135	3.05 (5.37)	0.35
New Trigrams	2,519	4.97 (6.62)	25,135	4.81 (8.03)	0.35
Novelty	2,519	0.97 (0.01)	25,135	0.97 (0.01)	0.57
Impact	2,519	1.03 (0.15)	25,135	1.03 (0.15)	0.74
Originality	2,519	0.54 (0.31)	25,135	0.54 (0.32)	0.73
Number of Claims	2,519	22.10 (17.56)	25,135	21.38 (18.95)	0.07*
Cites Received 1st Year	2,519	1.71 (3.90)	25,135	1.63 (4.27)	0.37
Cites Received 2nd Year	2,519	4.02 (7.11)	25,135	3.87 (7.81)	0.35

Appendix: Robustness Checks

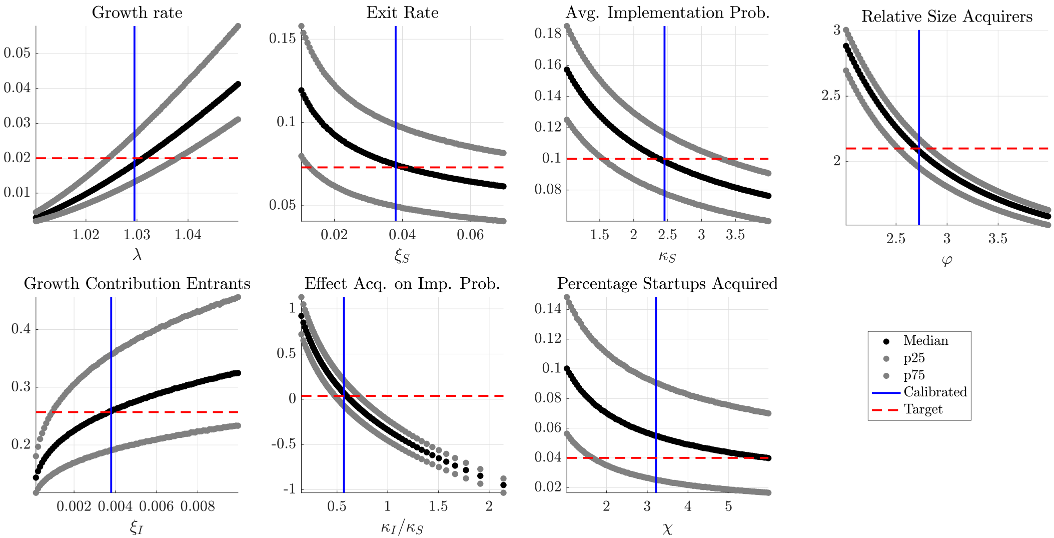
▸ Back to Empirics

Dependent variable: Number of citations received

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D(Post)	0.346***	0.343***	0.226***	0.392***	0.373***	0.541***	0.197***
	(0.019)	(0.020)	(0.017)	(0.023)	(0.018)	(0.021)	(0.006)
D(Treatment)	-0.010	-0.006	-0.007	-0.010	-0.009	-0.014	-0.006
	(0.035)	(0.034)	(0.034)	(0.045)	(0.029)	(0.039)	(0.012)
D(Post) * D(Treatment)	0.218***	0.223***	0.216***	0.263***	0.215***	0.419***	0.131***
	(0.041)	(0.041)	(0.042)	(0.061)	(0.032)	(0.083)	(0.025)
Observations	206,352	112,553	186,184	206,352	205,601	206,432	206,432
R-squared						0.297	0.287
Matched Pair FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Closest control patents		✓					
Pre & Post Year Window			✓				
No winsorization				✓			
Industry × Year FE					✓		
OLS: levels						✓	
OLS: logs							✓

Appendix: Global Identification Results

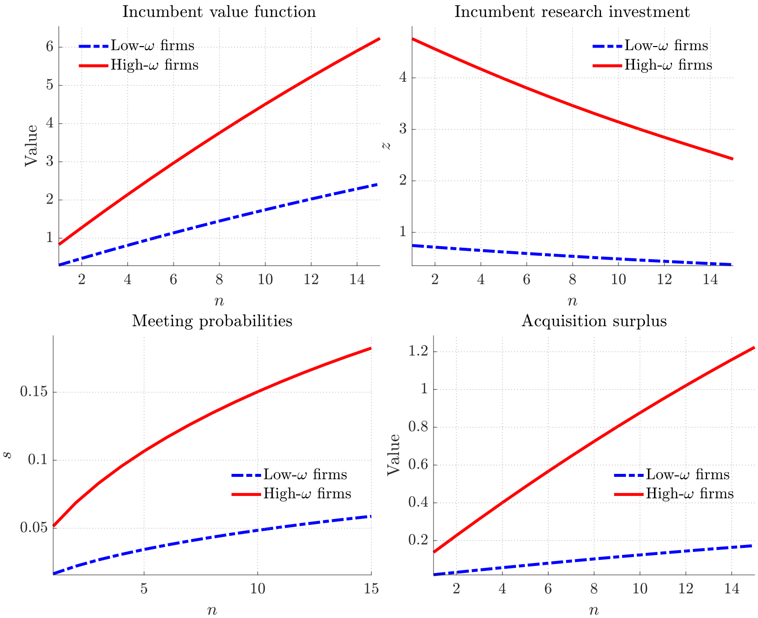
Back to Calibration



Notes: For each parameter-moment pair, we plot moments of the distribution created by underlying random variation in all remaining parameters. Good identification means (i) distribution co-moves with parameter; (ii) interquartile range is small; (iii) target falls close to median around calibrated value.

Appendix: Qualitative Features

Back to Calibration



Appendix: Computing Moments (1/3)

Back to Model Fit

- **Growth rate:** [2%]

$$g = \ln(\lambda) \sum_{\omega \in \Omega} \sum_{n=1}^{+\infty} \omega m(\omega, n) \Big[b_I(\omega, n) + (1+\gamma) b_S(\omega, n) \Big]$$

where

$$b_I(\omega, n) = z(\omega, n) i_I(\omega, n)$$
$$b_S(\omega, n) = x \Big(s(\omega, n) i_A(\omega, n) + \big(1 - s(\omega, n)\big) i_S(\omega) \Big)$$

are the arrival rates of innovations generated by incumbents (b_I) and startup (b_S) ideas.

Appendix: Computing Moments (2/3)

Back to Model Fit

- **Entry rate:** [7.3%]
  - In the data, entry rate is 7.3% (U.S. Census' BDS).
  - In the model, exit=entry, and there's entry if there's a startup, it is not acquired and it innovates, so:

$$
ExitRate = \sum_{\omega \in \Omega} \sum_{n=1}^{+\infty} m(\omega, n) x \Big(1 - s(\omega, n)\Big) i_S(\omega)
$$

- **Contribution of entrants to growth:** [25.7%]
  - In the data, innovation by entrants accounts for 25.7% of growth (Akcigit and Kerr (2018)).
  - In the model, we compute:

$$
ContEntGr = \frac{(1+\gamma)\ln(\lambda)}{g} \sum_{\omega \in \Omega} \sum_{n=1}^{+\infty} m(n, \omega) \omega x \Big(1 - s(\omega, n)\Big) i_S(\omega)
$$

Appendix: Computing Moments (3/3)

Back to Model Fit

- **Share of startup ideas that are acquired:** [4.0%]
  - In the Guzman and Stern (2020) data, 4% of innovative startups in the US get acquired.
  - In the model, we compute:

$$ShStartupIdeasAcq = \sum_{\omega \in \Omega} \sum_{n=1}^{+\infty} m(\omega, n) s(\omega, n)$$

Appendix: Consumption-Equivalent Welfare

▸ Back to Policy

- On the BGP, the welfare of the representative household is:

$$W = \frac{\ln(C_0)}{\rho} + \frac{g}{\rho^2}$$

- Then, we compute consumption-equivalent welfare between BGPs A and B as:

$$\varpi = \frac{C_0^A}{C_0^B} e^{\frac{g^A - g^B}{\rho}} - 1$$

where $A \equiv$ BGP with Acquisition Ban, and $B \equiv$ Baseline BGP.

- To implement this calculation, we normalize $a_{j,0} = 1, \forall j \in [0, 1]$.

Appendix: Partial Bans

Back to Policy

Change in outcome	**Acq. Ban**	**Ban** $n \geq 2$	**Ban** $n \geq 3$
Growth rate	$+1.6\%$	$+1.3\%$	$+0.7\%$
Incumbent own inn. rate	$+5.3\%$	$+4.9\%$	$+3.8\%$
Startup rate	-14.9%	-14.6%	-13.8%
Sales-weigh. % of impl. startup ideas	+8.4%	+8.3%	+7.8%
Frequency of acquisitions	-100%	-89%	-74%
Consumption-equiv. welfare	$+1.8\%$	$+1.6\%$	$+1.0\%$

Appendix: Accounting for non-competing acquisitions

Back to Policy

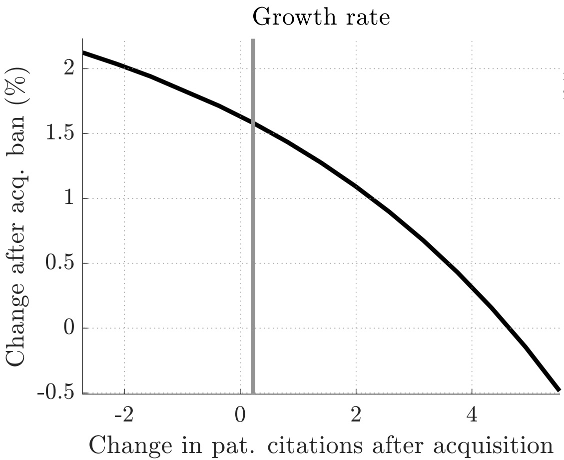
- Extended model with multiproduct firms.
- Incumbents can buy competing startups (as in the baseline), but also non-competing ones.
- We target 41% of competing acquisitions.
- Slightly smaller effect, driven by competiting acquisitions.

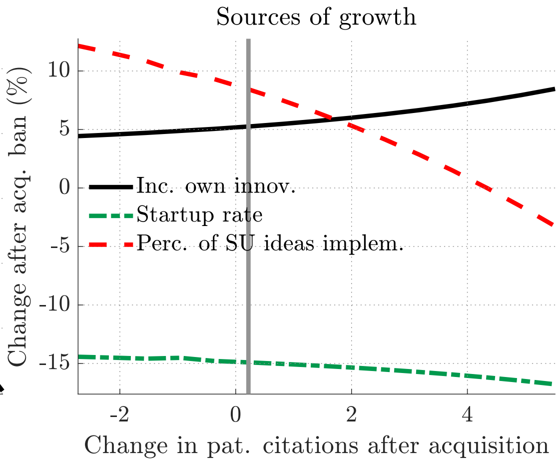
	Baseline	**Multiproduct**		
Change in outcome	*Acq. Ban*	*Acq. Ban*	*R Acq. Ban*	*U Acq. Ban*
Growth rate	+1.6%	+1.3%	+1.2%	+0.1%
Incumbent own inn. rate	+5.3%	+3.5%	+3.3%	+0.2%
Startup rate	−14.9%	−12.7%	−13.0%	+0.3%
Sales-weigh. % of impl. startup ideas	+8.4%	+9.8%	+10.3%	−0.4%
Frequency of acquisitions	−100%	−100%	−42%	−59%
Consumption-equiv. welfare	+1.8%	+1.7%	+1.6%	+0.1%

Appendix: Robustness – Calibration targets (1/2)

Back to Policy

- We re-calibrate the model to the same targets expect the causal impact of acquisitions on the implementation probability of startup ideas (β).



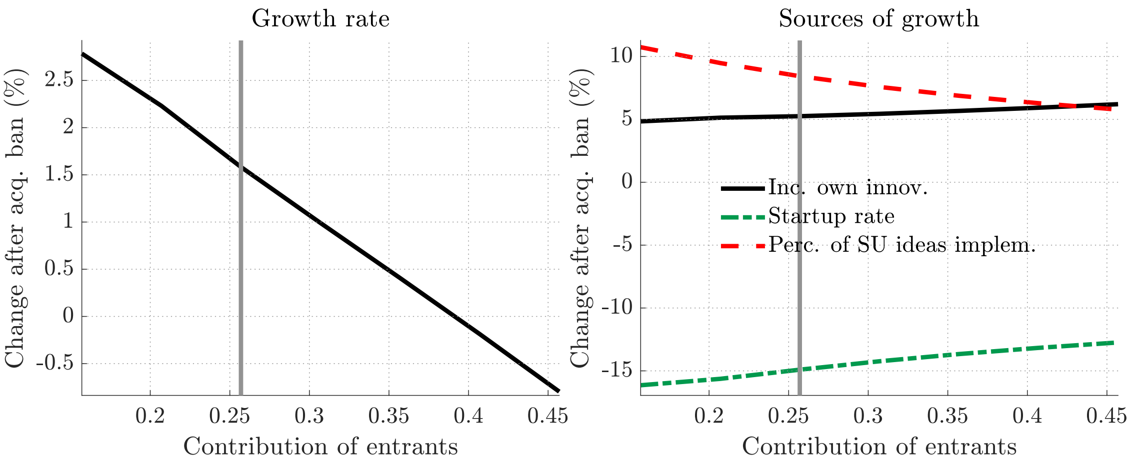


Notes: Each point in the plot is a different calibration of the model, where we only vary the target for the causal effects of acquisitions on the implementation probability of startup ideas.

Appendix: Robustness – Calibration targets (2/2)

Back to Policy

- We re-calibrate the model to the same targets expect the contribution of entrants to growth.

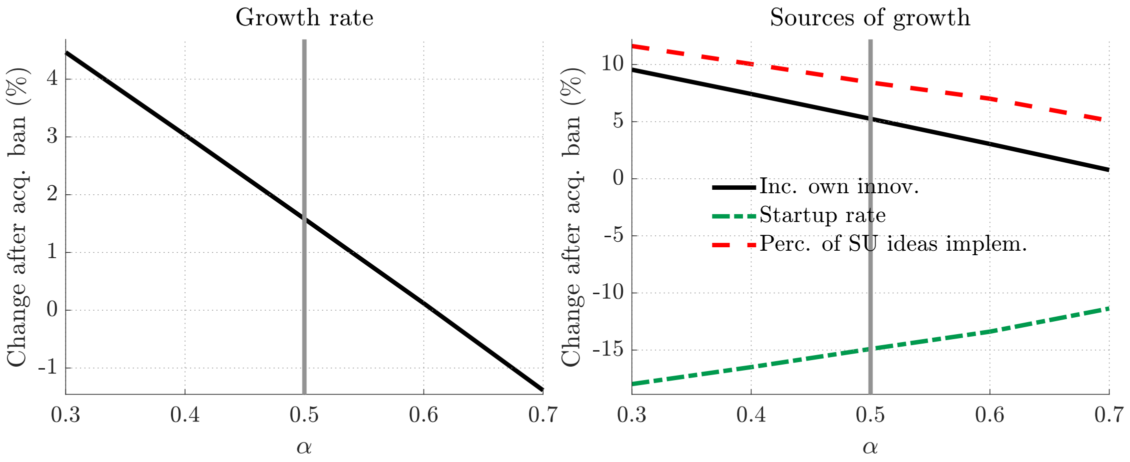


Notes: Each point in the plot is a different calibration of the model, where we only vary the target for the contribution of entrants to growth.

Appendix: Robustness – Parameters

Back to Policy

- We re-calibrate the model to the same targets but change the (externally-set) bargaining power of incumbents (α) parameter.



Notes: Each point in the plot is a different calibration of the model, where we only vary the (externally-set) bargaining weight on incumbents (α) parameter.