Do Startup Patent Acquisitions Affect Inventor Productivity? *

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We show that the acquisition of a startup inventor's first patent has a negative effect on the subsequent productivity of the patent's inventor, leading to 6.7 fewer patents being granted to the inventor over the following five years. This effect is not due to the inventors of acquired patents being able to focus on high-quality patents—in fact, the opposite appears to be the case. Our novel identification strategy is motivated by two new findings: Incumbent firms are more likely to acquire the patents of startups that patent examiners ask them to cite, and examiners are more likely to cite patents that they have reviewed in the past. When combined with the quasi-random assignment of patent applications to examiners, these two findings give rise to quasi-random linkages between startups and potential acquirers that help identify the causal effect of patent acquisitions on inventor productivity.

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1. Introduction

Even though startup acquisitions are common place (e.g., Ewens and Farre-Mensa, 2020), the welfare implications of these acquisitions are unclear. On the one hand, Phillips and Zhdanov (2013) argue that a more active M&A market encourages innovation by small firms, while enabling larger firms to optimally outsource R&D to them. Acquisitions also provide a key source of exit opportunities for founders and their investors, thereby incentivizing startup entry (Eisfeld, 2022) and financing (Phillips and Zhdanov, 2019). On the other hand, Cunningham et al. (2021) develop a model of "killer acquisitions" where incumbent firms acquire innovative targets to discontinue their projects and preempt future competition. Acquisitions of entrant firms by incumbents can also deter startup innovation and VC financing in the digital platform industry, by inducing potential early adopters to wait for the entrant's product to be integrated into the incumbent's instead of switching to the entrant (Kamepalli et al., 2021).

This paper seeks to enhance our understanding of the welfare implications of startup acquisitions by identifying their effect on the future innovation productivity of startup inventors. The challenge in identifying this effect is that acquisitions are endogenous. In particular, one concern is that acquirers may have information about the quality of the targets they pursue that is not observable to researchers. In such case, a naive ordinary least squares (OLS) regression would mistakenly capture acquirers' ability to select targets with high quality innovation prospects as a positive treatment effect of acquisitions. Alternatively, it is possible that only targets with limited innovation prospects are open to being acquired.[1] In the likely scenario that innovation prospects are not observable to researchers, a naive OLS regression would mistake such limited prospects for a negative treatment effect of acquisitions.

In order to overcome this endogeneity challenge, we use a novel identification strategy

[1]Startups tend to be closely held private firms. Thus, startup acquisitions typically require the acquiescence of their founders and other controlling shareholders.

that is motivated by the following three facts. First, around 20% of all patent citations are added by patent examiners during the examination process. Second, we show—for the first time in the literature—that examiners are more likely to add citations to patents that they recently reviewed relative to technologically similar patents reviewed by other examiners in the same USPTO art unit (patent examiners are organized in art units specializing in narrowly defined technology fields). Third, in many—but not necessarily all—art units, the assignment of patent applications to examiners is functionally random. These three facts combine to produce quasi-random linkages between startups and potential incumbent acquirers via shared patent examiners.

Our analyses support the identifying assumption that sharing a quasi-randomly assigned patent examiner generates exogenous variation in the likelihood that a startup is acquired by an incumbent firm—particularly if the incumbent firm is a historically active acquirer. We begin by showing that when an incumbent firm is asked by its patent examiner to cite a recently granted startup patent, the incumbent is more likely to go on to acquire that startup patent, all else equal. Building on this finding, we show that when an incumbent firm's patent and a startup's first patent share the same patent examiner, the incumbent firm is more likely to go on to acquire the startup's patent. Finally, we show that the likelihood that a startup's first patent is acquired by an incumbent firm patenting in the same art unit is increasing in the number of incumbent firms with whom the startup is linked via shared patent examiners.

Using these quasi-random examiner linkages as an instrumental variable (IV) for the likelihood that a startup patent is acquired by an incumbent firm, we show that startup patent acquisitions have a negative effect on the productivity of the patents' inventors. Specifically, we find that the acquisition of a startup inventor's first patent leads to 6.7 fewer patents being granted to the inventor over the next five years—a sizable effect given that the standard deviation of the five-year patenting rate of startup inventors is 5.5 patents. This effect operates exclusively at the intensive margin, as the effect of startup patent acquisitions on the probability that the patents' inventors are granted at least one more patent is small and insignificant.

The negative effect of patent acquisitions on inventors' subsequent patenting is not the result of inventors being able to focus on high-impact innovations after the sale of their startup patent to an incumbent reduces the inventors' financial constraints: In addition to patenting less, startup inventors whose patent is acquired also experience a decline in the overall number of citations that their subsequent patents receive and in the number of top-cited patents that they produce. The average number of citations per patent that their subsequent patents receive also decreases, although only marginally so.

Crucially, when we estimate naive OLS regressions that ignore the endogeneity of patent acquisitions, we find a highly significant positive partial correlation between patent acquisitions and an inventor's future patenting quantity and quality. The OLS results thus appear to be upward bias, consistent with the notion that higher quality inventors are more likely to have their patents acquired, all else equal. This apparent bias highlights the importance of our novel strategy to address the endogeneity of patent acquisitions.

Our identification strategy does rest on one crucial assumption: the quasi-random assignment of patent applications to examiners within the same art unit and year. Absent quasi-random assignment, our findings could reflect within-art unit technological specialization by patent examiners. In such case, patents reviewed by the same examiner would be technologically closer than other patents in the same art unit. This technological proximity could drive our IV's first stage, thereby undermining the exclusion restriction.[2]

While the assumption of quasi-random assignment of patent applications to examiners is shared by a number of recent papers (e.g., Sampat and Williams, 2019; Farre-Mensa et al., 2020; Feng and Jaravel, 2020), the evidence in Righi and Simcoe (2019) suggests that this assumption may not be valid in all art units. Reassuringly, we show that all our results are robust to focusing on the subsample of art unit-years that meet one of the following two

[2]Bena and Li (2014) show that acquisitions are more likely to happen between technologically close firms, and that acquirers technologically close to their target firms go on to produce more patents.

criteria for quasi-random examiner assignment: Patent applications are assigned to examiners based on the last digit of the sequentially assigned application number (as characterized by Feng and Jaravel (2020)), or they belong to the Computers and Communications areas, where Righi and Simcoe (2019) find little evidence of within-art unit examiner specialization.

Our paper makes three contributions. First, it enhances our understanding of the impacts of acquisitions. Prior work has found evidence of both positive and negative impacts of acquisitions on the performance of target firms. In addition to Phillips and Zhdanov's (2013) study discussed above, several other papers have emphasized the positive impacts of acquisitions. These include Li (2013), who shows that acquisitions increase the targets' productivity through more efficient use of capital and labor; Bena and Li (2014), who find that pre-merger technological overlap between merging firms leads to improved post-merger innovation output in the combined firms; and Li and Wang (2021), who show that post-merger collaboration between acquirer and target inventors is associated with more path-breaking patents than those filed by either acquirer or target inventor-only teams. One key difference between these four papers and ours is that they do not focus on acquisitions involving startups as targets—in fact, these prior studies focus exclusively on acquisitions involving publicly listed targets. Two recent studies analyze samples that include private targets, but they study different outcomes from ours: Kim (2022) shows that startup acquisitions substantially increase the rate of employee entrepreneurship, and Ma et al. (2022) show that after being acquired, target establishments invest more in technology.

On the negative side, Seru (2014) shows that public firms acquired by conglomerates in diversifying mergers experience a reduction in both the quantity and novelty of the patents they produce relative to merger targets whose acquisitions are not completed for exogenous reasons—an effect that is largely driven by inventors becoming less productive after the merger. Our paper shows that the negative effects of mergers identified by Seru (2014) extend beyond conglomerating mergers involving public targets. This was by no means a foregone conclusion, particularly in light of the papers discussed above—several of which use

Seru's (2014) same identification strategy—that have found positive impacts of acquisitions.

The negative effects we identify are also in line with the theoretical predictions of Cunningham et al.'s (2021) model of "killer acquisitions" aimed at preempting future competition, for which they find empirical support in the pharmaceutical industry. Our identification strategy allows us to identify the effects of startup acquisitions in a wide sample of industries, and our evidence supports Cunningham et al.'s (2021) hypothesis that their "core insights extend beyond [the pharmaceutical sector] specific setting" (p. 696).

Second, our paper introduces a novel identification strategy that can be helpful to researchers seeking to identify the causal impacts of acquisitions on innovative firms—regardless of whether the impacts are themselves innovation related. So far, researchers interested in identifying the causal impacts of acquisitions have relied on Seru's (2014) strategy of comparing completed acquisitions to acquisitions that are announced but end up failing for exogenous reasons. Seru's (2014) identification strategy is best suited to capture the consequences of acquisitions that are of sufficient size to give rise to public announcements that can be captured by financial databases such as SDC Platinum. By contrast, our identification strategy is particularly well suited to identify the effects of the acquisitions of innovative startups with only a few patented inventions—and thus only a limited number of quasi-random linkages to potential acquirers via shared examiners.[3]

Third, our paper identifies a novel channel via which incumbents can be made aware of startups in their industry: patent citations added by a shared patent examiner. In particular, the fact that examiner-added citations increase the probability that an incumbent acquires a startup's first patent suggests that entrepreneurs may benefit from taking this channel into account when deciding whether to rely on patents to protect their intellectual property.

[3]Relatedly, the most common reason for failure in Seru's (2014) control group of failed acquisitions are objections by regulatory bodies, which account for 44% of failed deals. Startup acquisitions are typically too small to trigger regulatory review (Cunningham et al., 2021).

2. Institutional Setting and Data

This section first describes the patent examination process, focusing on those institutional details that will play a key role in our identification strategy. We then describe the data sources used in our empirical analyses, discuss our sample construction process, and present summary statistics for our analysis sample.

2.1. The patent examination process

When an inventor applies for a patent at the United States Patent and Trademark Office (USPTO), the Office of Patent Application Processing (OPAP) assigns to it an application number and determines the application's USPC class and subclass based on its technology field.[4] In turn, the patent's technological classification determines the art unit to which the patent is assigned for review based on a concordance between classes/subclasses and art units.[5] Each art unit consists of several patent examiners who share a specialization in a narrowly defined technology field. Over our sample period, the USPTO employed some 13,500 examiners in over 700 art units.

Once a patent application reaches an art unit's holding queue, the art unit's supervisory examiner assigns the application to one of the unit's examiners for review. The precise details of the assignment process vary across art units. For example, Lemley and Sampat (2012) report that some art units assign patents to examiners based on the last digits of the application number; given that application numbers are assigned sequentially upon arrival by the OPAP, this assignment system is functionally random (Sampat and Williams, 2019). Other art units use a "first-in-first-out" rule: the application with the earliest filing date is assigned to the first available examiner. This quasi-random assignment of applications to examiners (conditional on art unit and year) underpins the identification strategies of several

[4]The class and subclass are determined through automated textual analysis of the application by a classification contractor.

[5]See https://www.uspto.gov/sites/default/files/documents/caau.pdf for the current version of the class/subclass-to-art unit concordance.

recent papers (Gaulé, 2018; Sampat and Williams, 2019; Farre-Mensa et al., 2020; Feng and Jaravel, 2020; Hegde et al., 2021)—and, as we discuss in Section 4, is also central to ours.

However, Righi and Simcoe's (2019) analysis suggests that not all art units follow a quasi-random process to assign patent applications to examiners: While Righi and Simcoe (2019, p. 138) note that "[t]here is no evidence that the broadest or most important applications are assigned to specific examiners," they do find evidence of technological specialization by patent examiners within certain art units. As explained in Section 3, all the findings in our paper are robust to excluding those art units where technological specialization by examiners is a concern, building on the approach pioneered by Feng and Jaravel (2020).

Once a patent application is assigned to an examiner's docket, the examiner is responsible for assessing whether the application's claims meet the legal thresholds of usefulness, novelty, and non-obviousness (35 U.S.C. §101-103) by comparing the claimed invention to the prior art, generally embodied in previous patents and publications.[6] In order to help examiners make this assessment, applicants have a "duty of candor" to cite any references "that a reasonable examiner would be substantially likely to consider important in deciding whether to allow an application to issue as a patent" (USPTO, 2020, Section 2001).

After applicants disclose their references, patent examiners conduct their own prior art searches, adding in particular citations to prior art with closely related or overlapping claims that may lead the examiner to limit (or reject) individual claims or entire applications. Since 1947, the front page of issued patents lists the prior art citations against which the patentability of the patented invention was judged. Importantly, since January 2001, it is possible to distinguish whether each listed citation was introduced by the applicant or was added by the examiner during the examination process (henceforth, "examiner-added citation"), as the latter are marked with an asterisk.

As we further explain in Section 3, our paper's identification strategy is motivated by the following two institutional facts. First, examiner-added citations are numerous: From

[6]This and the next paragraph draw largely on Alcácer et al. (2009, Section 2).

2001 through 2003, examiners were responsible for 40% of all citations made by U.S. patents (Alcácer et al., 2009). Second, despite considerable attempts at codification and standardization of patent examination procedures, the prior art search process that leads to examiner-added citations "remains largely idiosyncratic" (Alcácer et al., 2009, p. 417). As a result, "a significant portion of the overall variance among patents in ... the number and pattern of citations made ... can be explained by the identity of the examiner—in the language of econometrics, 'examiner fixed effects.' These examiner effects are significant even after controlling for the patent's technology field and its cohort" (Cockburn et al., 2004, p. 22). In particular, as Table 2 will show, examiners are more likely to add citations to patents they have themselves reviewed in the past.

2.2. Data sources

Our sample is built from a collection of datasets provided by the USPTO: the Patent Examination Research Dataset (PatEx), PatentsView, and the Patent Assignment Dataset—as well as the underlying raw XML files available from the USPTO's Bulk Data Storage System.

From PatEx, we collect application information for each patent, including the application's date and number as well as the examiner's name, unique identifier, and art unit.[7] We extend the application data through June 2021 by parsing the raw XML files. We use the same raw XML files to extract the set of all patent citations (including an indicator for whether each citation was added by the applicant or the examiner).

From the June 2021 version of the PatentsView dataset, we collect additional information for each patent grant, including all the patent's inventors and assignees as well as its technological classification. Importantly, PatentsView implements a disambiguation algorithm to assign a unique identifier to each inventor and assignee listed on a patent. This allows us

[7] The 2017 PatEx vintage contains a unique numerical identifier for each examiner. However, this identifier is absent in the 2019 and 2020 vintages. We infer examiner identifiers for all patents granted after the 2017 vintage coverage period using the examiner's first name, last name, and art unit. We conservatively drop all patents whose examiner we are unable to match in this way (e.g., those reviewed by an examiner that enters the sample after 2018).

to consistently track the innovative activity of firms and inventors over time.

From the Patent Assignment dataset, we collect the history of patent reassignments. For each reassignment action, the dataset reports the name of the assignor and assignee, the list of patents reassigned, and the execution date. The dataset also identifies the "nature of conveyance": e.g., assignment, merger, name change, correction, security interest (i.e., patents being pledged as collateral). In addition, the dataset includes an employer assignment indicator that identifies those instances where a patent is assigned by an inventor to her employer (see Marco et al. (2015) for additional details). We extent this dataset (which ends in December 2020) through August 2021 using the raw XML files.

2.3. Sample construction

While the USPTO PatentsView data generally has coverage back to the 1970s, a few key variables needed for our analyses (most notably, whether a patent citation was added by the applicant or the application's examiner) are not available prior to 2001. For this reason, we restrict our initial sample to utility patents granted to U.S. firms between January 2001 and July 2021, which yields a sample of 2.16 million patents. We identify patents granted to U.S. firms by requiring the assignee type in PatentsView to be a "US Company or Corporation."

A key group of interest throughout our analyses are firms that are first-time innovators. In order to identify them, we rely on the PatentsView assignee file, which contains a unique identifier for each patent assignee and thus allows us to track each firm's patenting history since 1976. Throughout our analyses, we focus on first-time innovators whose first patent was granted between January 2001 and June 2016; these filters result in a sample of 69,326 U.S.-based first-time innovating firms. Henceforth, for brevity, we will refer to such first-time innovating firms as "startups."[8]

In order to identify those instances when a startup's first patent is acquired, we proceed as follows. From the Patent Assignment dataset, we extract the reassignment history of each

[8]The June 2016 filter ensures that throughout our analyses, we are able to observe a full five-year history of post-first-patent outcomes for all first-time innovators.

startup's first granted patent.[9] Next, we identify those reassignment transactions that satisfy the following two conditions: (1) the nature of conveyance listed in the Patent Assignment dataset is "assignment" or "merger," and (2) they are not employer assignments.[10] As noted by Marco et al. (2015), these two conditions allow us to identify those patent reassignments that are most likely to reflect a real change in ownership—i.e., a patent acquisition. Finally, in the case of patents that go through several acquisition transactions, we focus only on the first one, to ensure that we are capturing the initial sale of the patent by its original assignee (as opposed to subsequent sales by subsequent owners).[11]

2.4. Final sample and summary statistics

Table 1 shows key summary statistics for the samples used in our empirical analyses. Panel A begins by reporting statistics on the number of patents and examiners for each art unit-year in our sample. The average (median) number of patents per art unit-year is 317 (299) and the average (median) number of examiners per art unit-year is 14.2 (14), with significant dispersion across art unit-years.

Panel B shows that the patents in our sample cite on average 17.52 other patents; of these citations, an average of 4.03 are added by the examiner. Both the total number of citations and the number of examiner-added citations exhibit substantial dispersion, with the two standard deviations greater than their respective means.

Panel C shows that 23.3% of the startups in our sample have their first patent acquired within five years of it being granted.

Panel D describes the patenting output of the inventors at the startups in our sample.

[9] If a startup is granted more than one patent on the date of its first grant, we focus on the patent with the earliest application date; we break any remaining ties randomly.

[10] We identify a transaction as an employer assignment if it is flagged as such in the Patent Assignment dataset, or if its execution date is within 60 days of the patent application date.

[11] Patents are sometimes sold to multiple firms within what is effectively the same transaction, but with slightly different record dates. We thus count as being part of the first sale all (ownership-changing) reassignments with execution dates within 30 days of the first reassignment. Throughout the paper, we use the terms patent "sale" and "acquisition" to include both transactions with a single acquirer as well as transactions with multiple acquirers that share the ownership and/or cash flow rights of the acquired patent.

Importantly, the USPTO data allow us to track the full patenting trajectory of each inventor, both prior to joining the startup and after leaving it. Specifically, for each startup, we consider all individuals who are listed as an inventor in one of the startup's first five patents as long as the patent's grant date is within one year of the startup's first patent grant. These inventors are granted an average (median) of 2.85 (1) patents within the five years following their first patent at the startup. Some of these inventors already had patenting experiencing prior to joining the startup, with an average (median) of 3.19 (0) prior patents to their name.

3. Examiner-Added Citations and Patent Acquisitions

The goal of this section is to establish two novel facts that are central to our identification strategy. First, in the course of reviewing a patent application, patent examiners are more likely to add citations to patents they have themselves reviewed in the past than to otherwise similar patents. Second, an incumbent firm is more likely to acquire a startup's first patent if the examiner reviewing one of the incumbent's own patent applications adds a citation to the startup's patent.

3.1. Are examiners more likely to cite patents they reviewed in the past?

We begin by documenting the frequent nature of examiner-added citations. Panel A of Figure 1 illustrates the distribution of examiner-added citations across art unit-years. For each art unit-year, we compute the fraction of citations found in patents granted in that art unit-year that were added by the examiner, and plot the resulting histogram of such fractions. The figure shows that examiner-added citations are relatively common, consistent with Alcácer et al. (2009): In the modal art unit-year, approximately 20% of all citations found in patents granted in that art-unit year have been added by the examiner; in over a quarter of all art unit-years, examiners are responsible for adding over 40% of all citations.

Examiner-added citations are even more common if we focus on citations to recently granted patents—the kind of patents that are most likely to involve competing innovations in active research areas. Indeed, Panel B of Figure 1 shows that, when we analyze citations to patents granted in the last five years, the distribution of the fraction of citations that have been added by the examiner shifts to the right and is centered around 50%. The results in Figure 1 thus highlight the widespread nature of examiner-added citations, pointing to an important channel via which examiners bring prior patents—particularly recent ones—to the attention of patent applicants during the process of challenging or limiting their claims.

With this stylized fact in hand, we now examine the extent to which an examiner is more likely to "self-cite"—i.e., to add citations to patents she has reviewed in the past. We begin by comparing the likelihood of an examiner adding cites to a patent she previously reviewed relative to a counterfactual random patent. In doing so, we control for the examiner's load of reviewed patents as well as for any variation taking place at the art unit-year level. Specifically, we first consider the cohort of patents reviewed by examiner e granted in art unit j in year t, P_{ejt}, and we count the total number of times the patents in the P_{ejt} cohort receive an examiner-added citation by a patent assigned to the same art unit j and reviewed by examiner e within the following five years. Next, we divide this count by the number of patents in the P_{ejt} cohort, yielding the five-year expected number of examiner-added self-citations received by a patent reviewed by examiner e granted in art unit j in year t (henceforth, the examiner self-citation rate).

To determine whether examiners are more likely to self-cite than to cite observably similar patents, we create a counterfactual cohort of patents for examiner e in art unit j in year t by exchanging each patent in each P_{ejt} cohort by a randomly chosen patent (without replacement) granted in the same art unit and year. This yields a set of counterfactual patent cohorts C_{ejt} which, by construction, have all the same size as the respective actual cohorts P_{ejt}. Finally, for each counterfactual cohort C_{ejt}, we calculate the counterfactual five-year examiner self-citation rate analogously to how we calculate the actual self-citation rate for the P_{ejt} cohorts: We count the total number of times the patents in the C_{ejt} cohort receive an examiner-added citation by a patent assigned to the same art unit j and reviewed by examiner e in years $t+1$ through $t+5$, and divide this count by the cohort size. Importantly, by using examiners' actual future review history, our counterfactual examiner self-citation rate controls for any changes in self-citation patterns that might be related to changes in the number of patents that examiners review over their lifecycle.[12]

Panel A of Figure 2 reports the cumulative distribution functions (CDFs) of the five-year examiner self-citation rate for the true observed set of patent cohorts P_{ejt} (blue line) and for the counterfactual cohorts C_{ejt} (red line), where the CDFs are calculated across examiner-art unit-years. To reduce noise, we restrict the sample to cohorts with at least 10 patents and require an examiner to stay a minimum of two additional years after year t in the same art unit. The uniformly higher CDF for the counterfactual cohorts relative to the true observed cohorts indicates that examiners are more likely to cite patents they previously reviewed than otherwise similar patents granted in the same art unit and year. For instance, only 5% of examiner-art unit-years in the counterfactual cohorts have a counterfactual examiner self-citation rate above 0.2 cites per patent; by contrast, as many as 38% of examiner-art unit-years have an actual examiner self-citation rate above 0.2 cites per patent.

3.1.1. The random examiner assignment subsample

Figure 2 aims to show that an examiner is more likely to cite a patent she previously reviewed over and above what would be expected based on technological grounds. For this conclusion to be valid, we need to assume that the assignment of patent applications to examiners within art unit-years is functionally random—a common assumption in the literature (Gaulé, 2018; Sampat and Williams, 2019; Farre-Mensa et al., 2020; Hegde et al., 2021). However, Righi and Simcoe (2019) argue that this assumption may not be valid in all art units, as in some art units there is evidence of within-art unit technological specialization by examiners. In such case, the evidence in Panel A of Figure 2 could reflect the fact that examiners are more

[12]This is important, as an examiner that transfers to a different art unit—or leaves the USPTO—three years after reviewing a patent will mechanically have less opportunities to add citations to that patent than if she had worked at the same art unit two additional years.

likely to cite patents that belong to their within-art unit area of specialization and thus are technologically closer, instead of reflecting examiners' tendency to self-cite.

To ensure that within-art unit specialization by examiners is not driving the results in Panel A of Figure 2, we repeat the analysis in a subsample that includes only those art units where examiner specialization is *not* a concern—henceforth, the "random examiner assignment subsample." This subsample, which we will use throughout the paper to address the examiner specialization concern, combines two sets of art unit-years. Following Feng and Jaravel (2020), the first set are art unit-years where the assignment of patent applications to examiners is determined by the last digit of the (sequentially assigned) patent application number. We identify these art unit-years following the same methodology as Feng and Jaravel (2020) (see Section A.2 in their Online Appendix).

Given that assigning applications to examiners based on the application number is only one of several random assignment methods followed by art units (Lemley and Sampat, 2012), we include a second set of art units in the random examiner assignment subsample: those in the Computers and Communications area.[13] This choice is motivated by Righi and Simcoe's (2019) finding that "[t]he degree of specialization varies across fields, with examiners in the Computers and Communications area exhibiting relatively little specialization compared to those in other TCs [technology centers]" (p. 146).

Panel B of Figure 2 redoes the analysis in Panel A within the random examiner assignment subsample. Specifically, for a cohort P_{ejt} (and its counterfactual counterpart C_{ejt}) to be included in Panel B, art unit j must belong to the random examiner assignment subsample in year t and in years $t+1$ through $t+5$. This ensures that both the initial cohort of patents P_{ejt} (and C_{ejt}) as well as the five years of future patents where we measure whether examiner e cites the patents in P_{ejt} (and in C_{ejt}) were quasi-randomly assigned to the examiner. The results in Panel B are indistinguishable from those in Panel A, thus indicating that exam-

[13]Specifically, art units belonging to technology centers 2100 ("Computer Architecture Software and Information Security"), 2400 ("Computer Networks, Multiplex, Cable and Cryptography/Security"), or 2600 ("Communications").

iners' tendency to self-cite is not driven by examiners specializing in reviewing applications belonging to specific subfields within certain art units.

3.1.2. Regression evidence

While providing the first evidence that examiners are more likely to add citations to patents they previously reviewed, Figure 2 is silent on the economic magnitude of this effect. We thus now turn to regression analysis to better capture the strength of examiners' self-citing tendency. We proceed as follows. First, for any patent i granted in art unit j in year t ("current" patents), we form all pairwise combinations between i and all patents k granted in art unit j in years $t-5$ through $t-1$ ("prior" patents). Next, we estimate OLS regressions within the sample of all pairwise combinations $\{i, k\}$, where the dependent variable is an indicator set equal to one if patent i has an examiner-added citation to patent k, and the key independent variable is an indicator set equal to one if patents i and k were reviewed by the same examiner.

Table 2 presents the results of this analysis, with coefficients scaled by a factor of 100 to maximize the number of significant digits shown, and with standard errors clustered at the art unit level. Panel A uses as the starting point the full sample of art unit-years. However, given the shear number of pairwise combinations $\{i, k\}$ possible, for tractability we randomly draw a 1% sample from that full sample and consider only current patents i from this random sample—as well as the full set of pairwise combinations $\{i, k\}$ involving each current patent i from the 1% sample.

The first specification in column 1 accounts for differences in the citation patterns across art units and time by including $Art\ unit \times Year$ fixed effects, where $Year$ denotes the grant year of the prior patent k (i.e., the potentially cited patent). The coefficient of 0.050 (t-stat=4.33) on the *Same examiner* indicator means that the likelihood of a patent having an examiner-added citation to a prior patent increases by 5 basis points (bp) if both patents were reviewed by the same examiner relative to other prior patents that were granted in the same art unit and year.[14] This represents a more than five-fold increase relative to the 0.91 bp unconditional likelihood of a patent having an examiner-added citation to a prior patent granted in the same art unit during the previous five years.

To ensure that this finding is not driven by general differences in the citing propensity of certain patent types or their examiners that are unrelated to examiners' self-citing tendency, the second specification adds current patent (i.e., citing patent) fixed effects.[15] The point estimate on the *Same examiner* indicator remains virtually unchanged following the addition of this new set of fixed effects (column 2). The same is true if we allow the patent-specific citation propensity to vary by the year of the potentially cited prior patent k by including $Patent \times Year$ fixed effects (column 3).[16]

Finally, we also control for potential variation in the propensity of a patent to cite prior patents based on the technological classification of the two patents in each current-prior patent pair $\{i, k\}$. Specifically, column 4 includes $Patent \times Year$ fixed effects as well as fixed effects for the interaction of the Cooperative Patent Classification (CPC) groups of the current and prior patents in each pair.[17] Following the inclusion of this new set of fixed effects, we see a slight decrease in the estimated coefficient of the *Same examiner* indicator to 4.1 bp and an increase in its precision (t-stat=4.60). The final specification extends the interacted CPC group fixed effects by further interacting them with the prior patent k's grant year, with similar results (column 5).

Panel B of Table 2 repeats the analysis in Panel A focusing only on those art unit-years within the 1% sample that belong to the random examiner assignment subsample in years $t-5$ through t, and so where within-art unit examiner technological specialization is not a concern.

[14] Alcácer and Gittelman (2006) show that, conditional on a patent citing a prior patent, the citation is more likely to have been added by the examiner than by the inventor if the citing and cited patent shared the same examiner. Our analysis is more general in that it does not condition on the set of realized patent citations, and so we are able to show that sharing an examiner increases the likelihood that a patent is cited in the first place—a finding that is central to motivate our identification strategy in the next section.

[15] These fixed effects are more granular than (and thus subsume) examiner fixed effects.

[16] These fixed effects subsume both the $Art\ unit \times Year$ and the patent fixed effects.

[17] An example of a CPC group is A43C, "fastenings or attachments of footwear; laces in general"; see https://www.uspto.gov/web/patents/classification/cpc/html/cpc.html for the full list of CPC groups. The interaction of the CPC groups in each current-prior patent pair results in 162,670 fixed effects.

Doing so reduces the point estimates on the *Same examiner* indicator by approximately 0.5 bp relative to Panel A—while, at the same time, their statistical significance increases. To illustrate, our most saturated specification in column 5 now shows that the likelihood of a patent having an examiner-added citation to a prior patent reviewed in the same art unit during the previous five years is 3.5 bp higher (t-stat=5.98) if the two patents share the same examiner—a more than three-fold increase relative to the unconditional mean. Thus, even in our most conservative specification, we continue to find that patent examiners' tendency to self-cite leads to an economically sizable increase in the likelihood that an examiner asks an applicant to cite a prior patent that the same examiner had previously reviewed. This tendency, when paired with the quasi-random assignment of patent applications to examiners, will be the source of exogenous variation that will allow us to identify the causal effect of patent acquisitions on the productivity of startup inventors.

We conclude this section by analyzing the heterogeneity of examiners' self-citation tendency across art units. Specifically, we re-estimate the column 4 specification separately for each art unit in our sample; in doing so, we do *not* not impose the 1% random sample restriction, so all art units are part of this analysis. Figure 3 reports the distribution of coefficients and t-statistics on the *Same examiner* indicator across art units.[18] Panel A reports the results for our full sample, while Panel B again focuses on the random examiner assignment subsample. Two patterns emerge from this figure. First, there appears to be some heterogeneity across art units in the effect of sharing a common examiner on the likelihood of having an examiner-added citation. Second, this heterogeneity notwithstanding, in virtually all art units examiners are significantly more likely to add citations to patents they reviewed in the past than to otherwise similar patents.

[18]Given that we run a separate regression for each art unit, here we cluster standard errors at the examiner level.

3.2. Are examiner-added citations associated with more patent acquisitions?

Having established the role of patent examiners' tendency to self-cite in determining examiner-added citations, we now turn to the relationship between examiner-added citations and patent acquisitions. Specifically, we now analyze whether incumbent firms that have been asked by an examiner to cite a startup's first patent are more likely to go on to acquire that patent. We emphasize that this analysis is purely descriptive, and so no causal inferences may be drawn from it.

In order to operationalize our analysis, we need to define the sets of potential target patents and their respective potential acquirers. First, we define the set of potential target patents as the first patent granted to each startup in our sample of first-time innovators. Second, for every startup patent in the set of potential targets, we define its set of potential acquirers as any firm that had been granted a patent in the same art unit that reviewed the startup patent within the five years prior to the startup patent's grant date. While our definition of a patent's set of potential acquirers is not exhaustive (virtually any firm can in principle acquire another firm's first patent), it results in a tractable number of incumbent firms whose proximity to the target patent's technology makes them natural potential acquirers of that patent.

Table 3, Panel A shows the results of estimating OLS regressions within the sample of all pairwise combinations between a startup's first patent and its potential acquirers. The dependent variable is an indicator set equal to one if the potential acquirer does indeed acquire the startup patent within five years of its grant date. The key independent variable of interest is an indicator set equal to one if at least one of the patents granted to the potential acquirer within five years of the startup patent's grant date has an examiner-added citation to the startup's patent. As in Table 2, we scale all coefficients by a factor of 100 for ease of interpretation, cluster standard errors at the art unit level, and estimate specifications with a growing set of fixed effects.

Column 1 begins by controlling for the general propensity of any particular incumbent firm to acquire startup patents—regardless of examiner-added citations—by including incumbent firm fixed effects. In addition, we also control for general time variation in the desirability of different technologies as acquisition targets by including fixed effects for $Art\ unit \times Year$ (of the startup's first patent). The estimated coefficient of 1.440 (t-stat=13.01) on the *Examiner-added citation* indicator means that incumbent firms that are asked by a patent examiner to cite a startup's patent are 1.4 percentage points (p.p.) more likely to go on to acquire the startup's patent.

Our findings in column 1 are robust to interacting the incumbent firm fixed effects both with the grant year of the startup patent (column 2) and with the interaction of the grant year and the art unit of the startup patent (column 3). The results are also robust to adding to the column 3 specification two new sets of controls that further account for differences in the extent to which certain technologies are attractive to potential acquirers: the interaction of incumbent firm fixed effects with fixed effects for the CPC technology group of the startup patent (column 4), and the interaction of incumbent firm fixed effects with fixed effects for the CPC technology group and for the grant year of the startup patent (column 5).

Panel B of Table 3 repeats the analysis in Panel A focusing only on startup patents granted in art unit-years that belong to the random examiner assignment subsample during both the grant year and the following five years. The point estimates decrease somewhat (by between 21% and 29% depending on the specification), but both their economic magnitude and their statistical significance remain large, with the smallest t-stat being 7.29.

The results in Table 3 thus point to a robust association between an incumbent firm being asked to cite a startup's first patent and the incumbent firm going on to acquire the startup's patent. While this association is consistent with our conjecture that examiner-added citations help put a startup's technology on an incumbent firm's radar, the association need *not* be causal: Our estimates in Table 3 may reflect the fact that incumbent firms are more likely to acquire patents that are technologically close to them (Bena and Li, 2014), and examiner-added citations could simply capture this technological proximity. The growing number of controls that we include in Table 3 alleviate but do not eliminate this concern.

Instead, in order to fully address this concern, we will adopt an identification strategy that leverages our findings in Section 3.1 regarding examiners' tendency to self-cite as a source of exogenous variation in examiner-added citations—and, as we will also show, in patent acquisitions. We do so in the next section.

4. The Effect of Patent Acquisitions on Startup Inventor Productivity

In this section, we first present our empirical strategy to identify the effect of patent acquisitions on the productivity of startup inventors. Next, we discuss our main findings.

4.1. Does sharing an examiner with an incumbent firm increase the likelihood that a startup's first patent is acquired?

In Section 3, we have established two novel facts: (1) a patent examiner is more likely to add citations to patents that she has reviewed in the past than to otherwise similar patents, and (2) examiner-added citations are associated with an increase in the likelihood that a startup's first patent is acquired. In this section, we build on these two findings to show that quasi-random links between startups and incumbents via shared patent examiners offer a source of exogenous variation in the likelihood that a startup's first patent is acquired.

We first examine whether when an incumbent firm has one of its patents reviewed by the same examiner that reviewed a startup's first patent, the incumbent is more likely to go on to acquire the startup's patent. In order to test this hypothesis, we construct the same pairwise sample of startup patents and potential acquirers as in Table 3. Specifically, we match the first patent granted to each startup in our sample of first-time innovators to all its potential established acquirers (defined as the set of all firms that had been granted a patent in the same art unit as the startup's first patent within the previous five years).

Using this sample of pairwise combinations, we estimate OLS regressions where, as in Table 3, the dependent variable is an indicator set equal to one if the potential acquirer does acquire the startup's first patent. However, Tables 3 and 4 differ in one critical aspect: In Table 3, the key independent variable was an indicator capturing whether the potential acquirer had an examiner-added citation to the startup patent—which could reflect technological proximity. By contrast, in Table 4, the key independent variable is an indicator equal to one if at least one of the patents granted to the potential acquirer within the five years following the startup patent's grant date was reviewed by the same examiner as the startup patent—which, conditional on the within-art unit random assignment of applications to examiners, is random.

Panel A of Table 4 presents the results for the full sample of art unit-years, as usual with coefficients scaled by a factor of 100 for ease of interpretation and standard errors clustered at the art unit level. The specifications are all analogous to Table 3, with the same sets of fixed effects introduced in the same sequence.

Specifically, in column 1, we begin by including incumbent firm fixed effects (thus controlling for the general propensity of any particular incumbent firm to acquire startup patents) and $Art\ unit \times Year$ fixed effects (thus controlling for time variation in the desirability of different technologies as acquisition targets). The estimated coefficient of 0.052 (t-stat=17.29) on the $Same\ examiner$ indicator means that the likelihood of a startup's first patent being acquired by an incumbent firm that has recently patented in the same art unit increases by 5.2 bp when the startup and the incumbent share a common patent examiner. This is a sizable increase given that the unconditional probability that an incumbent firm acquires a startup's first patent in our pairwise sample is 3.2 bp.

The inclusion of $Incumbent\ firm \times Year$ fixed effects in column 2 leaves the reported estimates from column 1 virtually unchanged. The same is not true when we include $Incumbent\ firm \times Art\ unit \times Year$ fixed effects in column 3, as doing so reduces the $Same\ examiner$ coefficient to 0.030. Still, the effect remains both statistically (t-stat=12.62) and economically strong, with the magnitude of the increase being similar to the 3.2 bp unconditional likelihood of an incumbent firm acquiring a startup patent in the sample. The inclusion of $Incumbent\ firm \times CPC\ technology\ group$ fixed effects in column 4, and of $Incumbent\ firm \times CPC\ technology\ group \times Year$ fixed effects in column 5 leads to similar point estimates (0.027 in both cases).

Columns 6 through 10 of Table 4 examine whether the effect of sharing a common examiner on the likelihood that an incumbent firm acquires a startup's first patent varies with the incumbent firm's past propensity to acquire patents. We expect an incumbent firm with a history of acquiring patents to be more likely to respond to an examiner asking it to cite a startup's first patent by acquiring that patent. To test this hypothesis, we augment each of the models in columns 1 through 5 by interacting the *Same examiner* indicator with an indicator set equal to one if the incumbent firm has acquired at least 10 patents over the previous five years.[19]

The results in columns 6 through 10 support the hypothesis that the effect of sharing an examiner on patent acquisitions is stronger for incumbent firms that have been active acquirers of other patents in the recent past. To illustrate, column 6 shows that in the case of incumbent firms with nine or fewer recent patent acquisitions, sharing the same examiner that reviewed a startup's first patent increases the likelihood that the incumbent firms goes on to acquire that startup patent by 3.7 bp (t-stat=14.61). This increase is 2.5 times larger, $3.7 + 5.6 = 9.3$ bp, if the incumbent firm has 10 or more recent patent acquisitions (the estimated coefficient of 0.056 on the interaction of the *Same examiner* and the *Frequent acquirer* indicators is highly significant, t-stat=7.73). As in columns 2 through 5, the inclusion of additional fixed effects in columns 7 through 10 leads to smaller but still statistically and economically significant estimates.

Overall, the results in Table 4 show that startup patents that share a common patent examiner with an incumbent firm that has recently patented in the same art unit are more likely to be acquired by that incumbent firm than by otherwise similar incumbents with whom they do not share an examiner—particularly if the incumbent firm has an active

[19]The uninteracted *Frequent acquirer* indicator is subsumed by the incumbent firm fixed effects.

history of acquiring patents. Panel B in Table 4 shows that these findings are robust—if anything, they become larger in magnitude—when we restrict our analysis to target patents granted in art unit-years that belong to the random examiner assignment subsample during both the grant year and the following five years. Crucially, in these art units, within-art unit examiner specialization is not a concern, thus ensuring that our results are not the result of closer technological proximity between patents that share the same examiner.

4.2. Shared examiners as source of exogenous variation in patent acquisitions

Our goal is to analyze the effect that the acquisition of one of a startup's first patents has on the subsequent productivity of the startup's inventors. This question is complicated by the fact that patent acquisitions are endogenous—that is to say, they are likely to be correlated with unobservable variables that can themselves impact inventor productivity. For instance, one possibility is that patents that are acquired tend to be of higher quality than those that are not acquired; in the likely event that patent and inventor quality are correlated, this would bias our naive OLS estimates of the effect of patent acquisitions on inventor productivity upward. On the other hand, it is possible that those startups that choose to sell their patents tend to be working on projects with limited prospects or whose employees are less committed to continue innovating in the future; in such cases, our naive OLS estimates would be biased downward.[20]

In order to identify the effect of patent acquisitions on the productivity of a startup's inventors, we exploit our finding in Table 4 that a startup's first patent is more likely to be acquired by an incumbent firm if they share the same patent examiner. Under the assumption that the within-art unit assignment of patent applications to examiners is quasi-random, shared examiners provide a source of exogenous variation in patent acquisitions that we can use to identify how acquisitions affect the productivity of startup inventors.

While suggesting that this identification strategy is potentially viable, the results in Table

[20]While both sources of bias may operate simultaneously, they are unlikely to perfectly offset each other.

4 on their own are not sufficient for our purposes: We need to find a source of exogenous variation in the overall likelihood that a startup's first patent is acquired by *any* incumbent firm, whereas Table 4 shows an increase in the likelihood that a *particular* incumbent firm acquires a startup's first patent when the two share a common patent examiner. To obtain a source of exogenous variation that operates at the startup level instead of at the level of each specific startup-incumbent pair, we aggregate the number of linkages via shared patent examiners that each startup in our sample has to incumbents in its industry as follows:

$$N\ linked\ incumbents_{ijt} = \sum_{a \in A_{jt}} \max_{p \in P_{aj}} [1\{E(i) = E(p)\} \times 1\{M(i) + 12 \leq M(p) \leq t + 48\}]$$

where, for any patent p, $E(p)$ and $M(p)$ identify its examiner and application month, respectively. Further, for any firm a, we define P_{aj} as the set of all patents granted to a in art unit j.

Thus, for each startup patent i granted in art unit j in month t, *N linked incumbents* counts the number of incumbent firms with whom the startup patent is linked via a shared patent examiner that satisfy the following characteristics. First, we focus on incumbent firms with one or more patent grants in art unit j in the trailing five years. Second, we require incumbents to be frequent acquirers (defined as firms with at least 10 patent acquisitions over the previous five years), motivated by our finding in Table 4 that frequent acquirers are more prone to acquire a startup's patent when sharing a common examiner. Accordingly, we define A_{jt} to be the set of frequent acquirers that have patented in art unit j during the prior five years.

Third, for an incumbent firm in A_{jt} to be linked to startup patent i via a shared examiner, we require the incumbent to have been granted a patent p in i's art unit j that was (1) reviewed by the same examiner as patent i (and thus $1\{E(i) = E(p)\} = 1$) and (2) whose application date was at least 12 months after patent i's application date and no more than 48 months after i's grant date (and thus $1\{M(i) + 12 \leq M(p) \leq t + 48\} = 1$). By requiring that p's application date followed that of the startup patent by at least 12 months, we aim to ensure that the shared examiner has had a chance to become familiar with the startup's patent (and thus can potentially cite it) by the time she reviews the incumbent's patent p. Our additional requirement that p's application date be no more than 48 months after the startup patent's grant date is meant to allow enough time for the incumbent to become aware of the startup patent via their shared examiner during p's review and to pursue its acquisition within five years of the startup patent's granting (five years being the time frame during which we measure startup patent acquisitions throughout the paper).

With the *N linked incumbents* measure in hand, we now examine the extent to which being linked to more frequent-acquirer incumbents via a shared examiner increases the probability that a startup's first patent is acquired. Table 5, Panel A presents the results of OLS regressions estimated in our full sample of startups, where the dependent variable is an indicator set equal to one if a startup has its first patent acquired within five years of its granting. As in earlier tables, we scale coefficients by 100 and cluster standard errors at the art unit level. Moreover, we standardize our key variable of interest, *N linked incumbents*, to facilitate the economic interpretation of the results.

Column 1, which includes fixed effects for the art unit of each startup's first patent interacted with fixed effects for the patent's grant year, shows that startup patents that are linked to more incumbents via a shared examiner are more likely to be acquired: The coefficient on *N linked incumbents* indicates that a one standard deviation increase in the number of frequent-acquirer incumbents that have a patent examined by the same examiner who reviewed a startup's first patent increases the likelihood of the patent being acquired within five years by 1.98 p.p. (t-stat=7.09). This represents an 8.5% increase relative to the 23.3% unconditional five-year acquisition rate in our sample. We find similar results when we add fixed effects to control for the startup patent's CPC technology group in column 2, and when we further interact these technology group fixed effects with fixed effects for the startup patent's grant year in column 3.

To ensure that our findings in columns 1 through 3 are not driven by outliers, columns 4 through 6 report analogous analyses with the logarithm of one plus *N linked incumbents* as the key independent variable (again standardized). Our conclusions remain unchanged, with the relation between the logged number of linked incumbents via shared examiners and the likelihood that a startup's first patent is acquired exhibiting a similar economic magnitude as the non-logged version. If anything, the larger t-statistics indicate that the log transformation leads to more precisely estimated coefficients.

Panel B in Table 5 shows that our findings are again robust to restricting our analysis to startups whose first patent was granted in art unit-years belonging to the random examiner assignment subsample during both that first patent's grant year and the following five years.

Overall, Table 5 shows that the effect of sharing a common examiner on the likelihood of being acquired does indeed aggregate up to the startup patent level across different potential acquirers. Such quasi-random shared examiner linkages between startups and potential acquirers offer a promising source of plausibly exogenous variation to identify the effect of patent acquisitions on the innovation activity of startup inventors.

4.3. Do startup patent acquisitions affect inventor productivity?

What are the consequences for a startup and its inventors of having one of the startup's first patents acquired by an established competitor? When considering the potential effects on the future productivity of the startup's inventors, even the *sign* of the net effect is arguably unclear. On the one hand, the sale of the patent is likely to bring about an influx of capital to the startup, thus providing it with additional resources to fund its future inventions.

On the other hand, the patent sale may hamper the startup's future innovation efforts by depriving it from a key building block for such efforts. In particular, this could be the case if the acquirer uses the acquisition to preempt future competition (as in Cunningham et al.'s (2021) "killer acquisitions"), or if the patent sale creates doubt in the minds of prospective customers regarding the startup's future viability and deters them from adopting its products

(Kamepalli et al., 2021). The sale could also have a negative impact on the motivation of the startup's inventors if it offers them an early opportunity to cash out. As discussed above, identifying these effects is notoriously challenging due to the endogenous nature of patent acquisitions, which are likely to be correlated both with the unobserved quality of the underlying innovations and with the inventors' willingness to sell.

4.3.1. Effect on future patenting quantity

We begin by examining the relationship between startup patent acquisitions and future patenting quantity. In order to provide a benchmark for our IV analyses, Table 6 first examines the association between acquisitions and future patenting in an OLS setting. Throughout the table, we cluster standard errors at the art unit level and include the same controls as in the most stringent specification in Table 5: fixed effects for the art unit of each inventor's first patent interacted with fixed effects for the patent's grant year, as well as fixed effects for the first patent's CPC technology group again interacted with grant year fixed effects.

Our analysis is at the inventor level, and our sample includes those individuals meeting the following two criteria: (1) the individual is listed as an inventor in one of a startup's first five patents, and (2) that patent's grant date is within one year of the startup's first patent grant. In the case of startup inventors with more than one patent satisfying these criteria, we focus on their first granted patent while working at the startup. In the case of inventors patenting at more than one startup, we only include subsequent patents if at least three years have elapsed since their first patent at their prior startup (our conclusions are robust to using alternative cutoffs).

The first two columns examine the partial correlation between having a startup inventor's first patent acquired within five years of it being granted and the number of patents granted to the inventor during the five years following the granting of that first patent.[21] We find that this partial correlation is positive and highly significant, with the acquisition of an inventor's

[21] Recall that the USPTO data allow us to track the full patenting trajectory of each inventor, regardless of whether she continues working at the startup or moves elsewhere.

first patent being associated with 0.40 more future patents (t-stat=7.14). Perhaps in a sign that this correlation reflects ex ante differences in the quality of inventors whose patents are acquired rather than the causal effect of acquisitions, column 2 shows that the estimated correlation between acquisitions and future patents goes down by 59% when we control for the number of patents granted to the inventor prior to joining the startup—though the correlation still remains positive and significant (t-stat=3.24).

In the remaining columns, we explore the extensive and intensive margins of the partial correlation between patent acquisitions and future patenting. More precisely, in columns 3 and 4 the dependent variable is an indicator set equal to one if the inventor is granted at least one patent in the following five-year period; in columns 5 and 6, the dependent variable is the logarithm of the number of patents granted to the inventor over the following five years, which restricts our analysis to inventors that are granted at least one subsequent patent. We continue to find positive and strongly statistically significant estimates throughout.

The results in Table 6 paint a clear picture: Ignoring the endogeneity of patent acquisitions would lead us to conclude that patent acquisitions provide a positive boost to the productivity of startup inventors, both at the extensive and intensive margins.

However, it is unlikely that startup patent acquisitions are orthogonal to the (unobservable) quality of the startup's inventors, and so the results in Table 6 cannot be interpreted causally. To address this endogeneity challenge, we leverage our finding in Table 5 that quasi-random linkages between startups and incumbent firms via shared patent examiners offer an exogenous source of variation in startup patent acquisitions that is unrelated to the fundamental value of the startup's innovations or its strategic choices. Specifically, Table 7 examines the effect of a startup inventor's first patent being acquired on the inventor's future patenting in a two-stage least squares (2SLS) framework, where in the first stage we instrument patent acquisitions with *N linked incumbents* (defined as in Table 5). In each column, Panel A of Table 7 reports the second-stage results for the exact same model and sample analyzed in Table 6. In addition, for each second-stage model, Table 7 also shows the respective first-stage Kleibergen-Paap *rk* Wald F statistic, which in all 2SLS regressions reported in the paper is above the critical value of 10 (Stock and Yogo, 2005).

Addressing the endogeneity of startup patent acquisitions leads to opposite conclusions to those found in our OLS analysis. Indeed, column 1 in Table 7, Panel A shows that the acquisition of a startup inventor's first patent leads to 4.36 less patents being granted to the inventor over the next five years (t-stat=-2.07). This is a sizable decrease given that the standard deviation of the five-year patenting rate for inventors in our sample is 5.48 patents. We find a more pronounced (-6.66 patents) and more significant (t-stat=-3.12) effect in column 2, where we control for the number of patents granted to the inventor prior to joining the startup.

Interestingly, columns 3 and 4 show that there is no significant extensive margin effect of patent acquisitions on the likelihood that an inventor patents again after the acquisition (t-stat=-0.20 and -1.04, respectively). But the intensive margin effect of patent acquisitions on future patenting is strongly negative: Column 5 shows that patent acquisitions lead to a 57.9% ($= e^{-0.865} - 1$; t-stat=-2.34) decrease in future patenting for those inventors with at least one future patent; when we control for past inventor productivity in column 6, the decline is even more pronounced, -69.8% ($= e^{-1.196} - 1$; t-stat=-3.30).

Panel B of Table 7 shows that all our conclusions from Panel A are robust to restricting our analysis to inventors patenting in art unit-years that belong to the random examiner assignment subsample. Crucially, here our IV's exclusion restriction is not threatened by the possibility that within-art unit examiner specialization could imply that inventors whose first patent is linked to more incumbent firms via shared examiners might work in areas technologically closer to those incumbents. In fact, the negative effect of patent acquisitions on the number of future patents granted to an inventor all but doubles in this subsample, and the effect continues to operate exclusively via the intensive margin.

4.3.2. Effect on future patenting quality

Our findings in Table 7 raise the possibility that the negative intensive margin effect of startup patent acquisitions on inventors' future patenting is due to the fact that after selling their initial patent, inventors are able to focus on high-impact innovations. This could be the case if the patent sale means that inventors become less financially constrained, perhaps due to the cash infusion or because now they work for the (well-funded) acquirer. In such case, we would expect the inventor to be granted fewer but higher quality subsequent patents.

In order to explore this possibility, Tables 8 and 9 investigate the association between the acquisition of a startup inventor's first patent and various measures of the inventor's patenting quality during the five years following the granting of that first patent. Our analyses are based on the same samples used in Tables 6 and 7; the fixed effects are also the same, and in this case we report only models that control for the inventor's number of prior patents to conserve space.

Table 8 reports the results of estimating OLS regressions while Table 9 reports 2SLS results with the same IV (*N linked incumbents*) as in Table 7. Panel A in Table 9 again focuses on the full sample and Panel B on the random examiner assignment subsample. Regardless of how we measure quality, the OLS results in Table 8 show a positive partial correlation between patent acquisitions and an inventor's future patenting quality—though of course no causal interpretation can be drawn from these results.

In contrast to our OLS findings, column 1 in Table 9, Panel A shows that startup patent acquisitions lead to the subsequent patents granted to the inventor receiving a total of 11.95 fewer scaled citations (t-stat=-2.26)—and 23.68 fewer scaled citations in Panel B (t-stat=-2.22). (As is customary when working with citation-based measures of patent quality (e.g., Bernstein, 2015), throughout the table we scale each patent's citation count by the average number of citations received by patents granted in the same CPC technology group and year.) The dependent variable in column 2 is the same as in column 1 but in logarithm form, which restricts our sample to inventors that are granted at least one future patent and at least one of these patents receives one citation. This intensive margin analysis shows that patent acquisitions reduce future citations by 86.5% ($= e^{-1.999} - 1$; t-stat=-2.81) in Panel A and by 96.7% ($= e^{-3.413} - 1$; t-stat=-2.48) in Panel B.

In order to better separate the effect of acquisitions on the overall quantity and quality of subsequent patents an inventor is granted, columns 3 and 4 focus exclusively on top-cited patents. Specifically, we define a patent as top cited if the number of citations it receives is in the top 10% (column 3) or the top 5% (column 4) of citations received by patents granted in the same CPC technology group and year. In Panel A (full sample), we find that patent acquisitions lead to inventors being granted 1.80 fewer top 10%-cited patents (t-stat=-2.48) and 0.95 fewer top 5%-cited patents (t-stat=-2.09) over the following five years. These negative effects almost double in size in Panel B (random examiner assignment subsample).

In columns 5 and 6, we also find negative but noisier effects of patent acquisitions on the average quality of startup inventors' subsequent patents. Specifically, the dependent variable in column 5 is an indicator set equal to one if the average number of scaled citations per patent received by the patents granted to the inventor is greater than one; thus, this indicator identifies whether the average patent granted to the inventor within five years of its first patent grant is of above-average quality, i.e., it has more citations than the average number of citations received by patents granted in the same CPC technology group and year. To be included in column 5, an inventor needs to have been granted at least one future patent. In Panel A, we find that startup patent acquisitions decrease the likelihood that the average quality of an inventor's subsequent patents is above average by 23.9 percentage points, though this estimate is not statistically significant (t-stat=-1.53). The estimated decrease in Panel B is more pronounced (54.5 p.p.) and marginally significant (t-stat=-1.75).

Finally, in column 6, the dependent variable is the logarithm of the average number of scaled citations per patent received by the patents granted to the inventor during the following five years. To be included in column 6, an inventor needs to have been granted at least one future patent and at least one of these patents needs to have received one citation.

We find that patent acquisitions reduce the number of scaled citations of the average future patent by a marginally significant 53.7% ($= e^{-0.771} - 1$; t-stat$=-1.75$) in Panel A; the decrease is larger ($-69.3\% = e^{-1.182} - 1$) but insignificant (t-stat$=-1.41$) in Panel B.

Taken together, the results in Table 9 indicate that the negative effect of startup patent acquisitions on inventors' future patenting quantity is not the result of inventors focusing on high-impact innovations—rather the opposite. Startup patent acquisitions not only lead startup inventors to patent less, but they also reduce the overall number of citations that the inventors' subsequent patents receive, the number of top-cited patents the inventors produce, and they even marginally reduce the average number of citations per patent their patents receive.

5. Conclusions

We show that the acquisition of a startup inventor's first patent leads to 6.7 fewer patents being granted to the inventor over the next five years—a sizable effect given that the standard deviation of inventors' five-year patenting rate is 5.5 patents. This effect operates exclusively at the intensive margin, as startup patent acquisitions have a small and insignificant effect on the probability that the patent's inventor receives at least one more patent. The negative effect of patent acquisitions on inventors' future patenting quantity is not the result of inventors focusing on high-impact innovations—if anything, the opposite is the case.

Our novel identification strategy exploits quasi-random linkages between startups and potential acquirers that operate via shared patent examiners to address the endogeneity of patent acquisitions. Doing so is crucial, as naive OLS regressions yield a positive partial correlation between patent acquisitions and an inventor's future patenting quantity and quality. Our strategy is built around two new findings: Incumbent firms are more likely to buy the patents of startups that patent examiners ask them to cite relative to technologically similar patents, and examiners are more likely to cite patents they have reviewed in the recent past. Together with the fact that many USPTO art units assign patent applications to examiners quasi-randomly, these two new findings give rise to exogenous variation in the likelihood that a startup patent is acquired by an incumbent firm, thus allowing us to identify the causal effects of acquisitions.

Our findings add to a growing body of knowledge that has examined the effects of acquisitions on the future performance of target firms, finding both positive (Li, 2013; Phillips and Zhdanov, 2013; Bena and Li, 2014; Li and Wang, 2021; Kim, 2022; Ma et al., 2022) and negative consequences (Seru, 2014; Cunningham et al., 2021). A key distinctive feature of our identification strategy is that it is particularly well suited to identify the effects of acquisitions involving innovative startups, whose acquisitions can have outsize consequences on an industry's innovation trajectory and competitive structure but that are poorly suited to be studied with Seru's (2014) influential strategy.

The current draft of this paper leaves one major question unanswered: What mechanisms drive our findings? In particular, to what extent are the negative acquisition effects we identify the result of strategically motivated "killer acquisitions," or of inventors' reduced incentives after cashing out? We hope to shed light on these questions in future drafts.

At the same time, we emphasize that our study does not seek to provide a comprehensive welfare analysis of startup patent acquisitions. There are other potential effects of such acquisitions that fall beyond the scope of our study—most notably, their impact on entrepreneurs' and investors' incentives to found and support new startups, respectively (Eisfeld, 2022; Phillips and Zhdanov, 2019). That being said, the negative inventor productivity effects we identify do point to an important societal cost of startup acquisitions that needs to be part of any such welfare analysis, and they highlight the importance of ensuring that these acquisitions do not fall under the radar of antitrust regulators.

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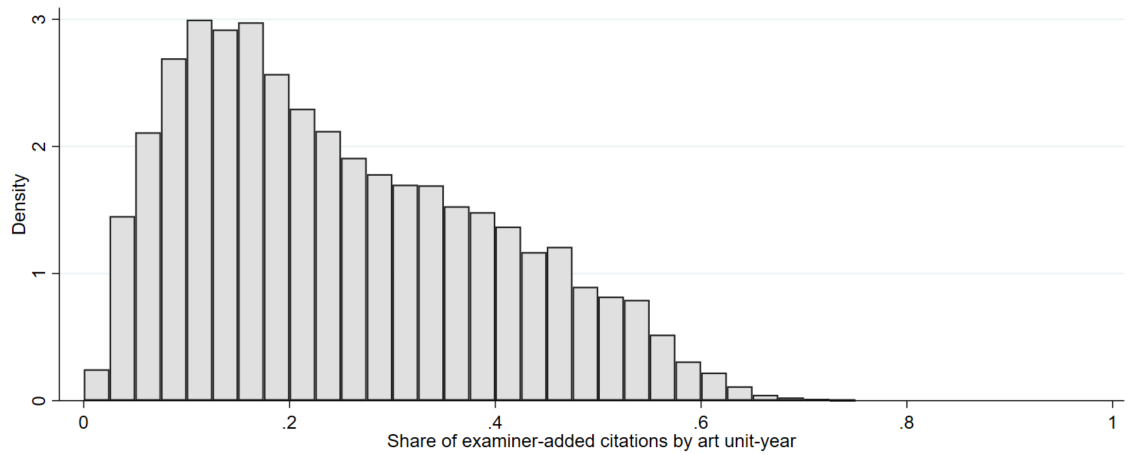
Panel A: Citations to all previous patents



Panel B: Citations to patents granted within the previous five years

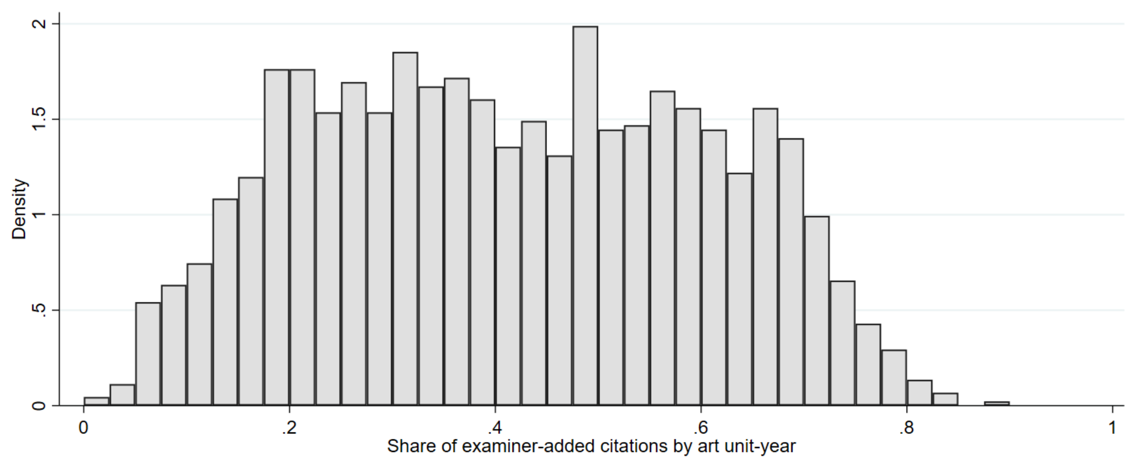
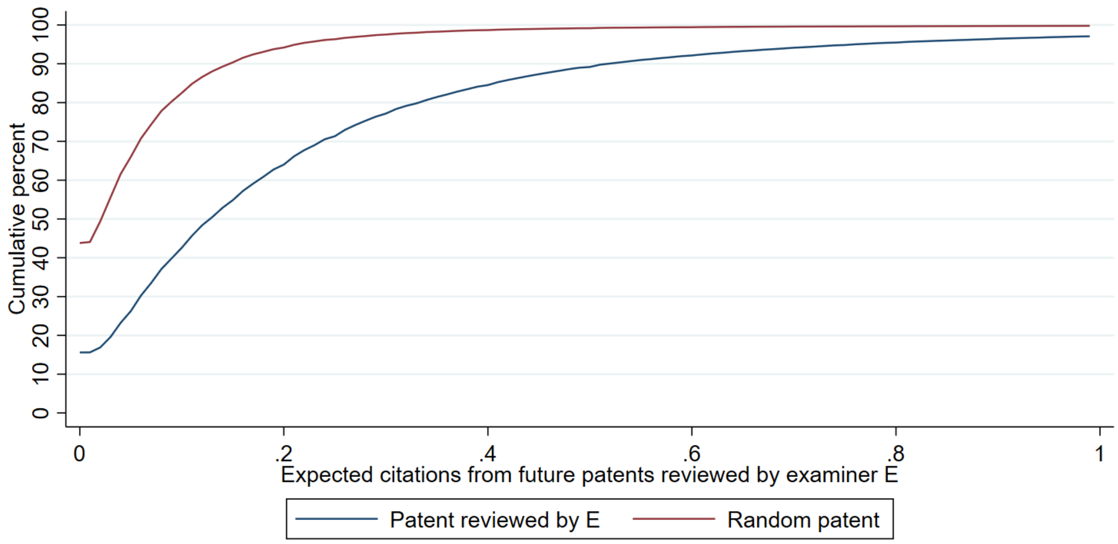


Figure 1. Share of examiner-added citations.
This figure shows the fraction of citations that are added by the patent examiner across the art unit-years in our sample. Panel A considers all citations, while Panel B focuses on citations to patents granted within the previous five years.

Panel A: Full sample



Panel B: Art unit-years in the random examiner assignment subsample

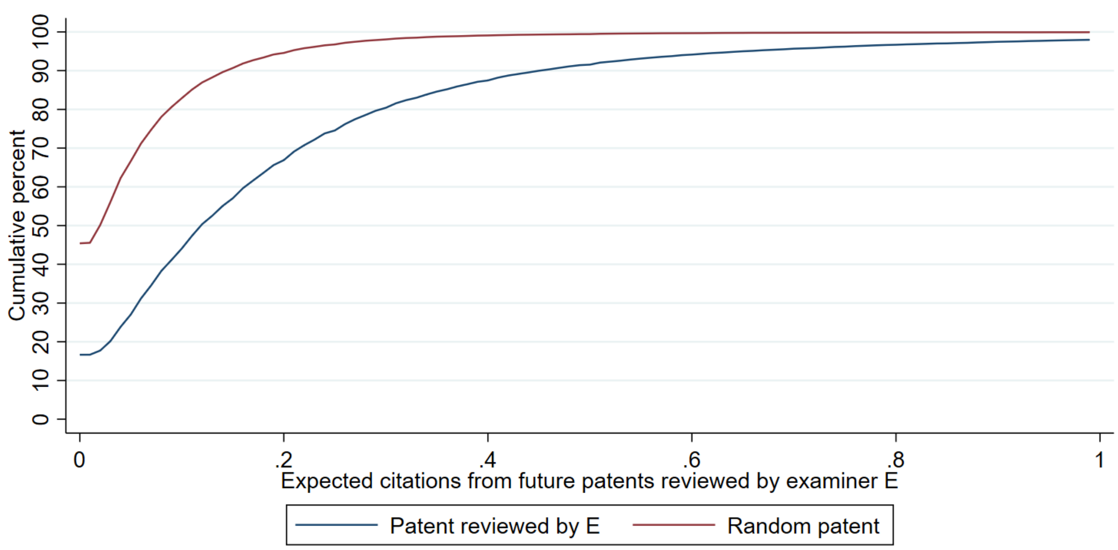
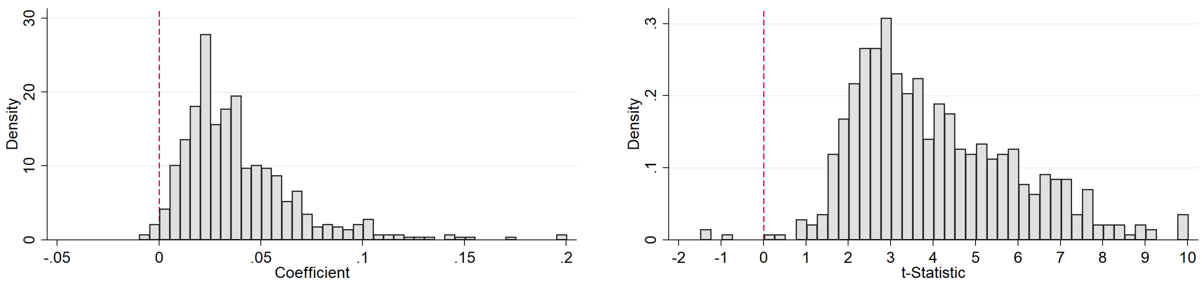


Figure 2. Examiner self-citation rate vs. randomized citation rate. This figure examines the extent to which examiners are more likely to add citations to patents they have reviewed in the past. In Panel A, the blue line reports the cumulative distribution function (CDF) of the examiner self-citation rate for the examiners in our full sample of art unit-years. For each examiner-art unit-year, the examiner self-citation rate is the expected number of cites that the patents reviewed by that examiner will receive from patents reviewed by the same examiner during the next five years. We compare this self-citation rate with the number of cites that a random patent from the same art unit-year expects to receive from patents reviewed by that same examiner; the red line shows the CDF of such randomized citation rates. Panel B redoes the analysis in Panel A including only art unit-years belonging to the random examiner assignment subsample, where within-art unit examiner technological specialization is not a concern (see Section 3.1.1 for details).

Panel A: Full sample



Panel B: Art unit-years in the random examiner assignment subsample

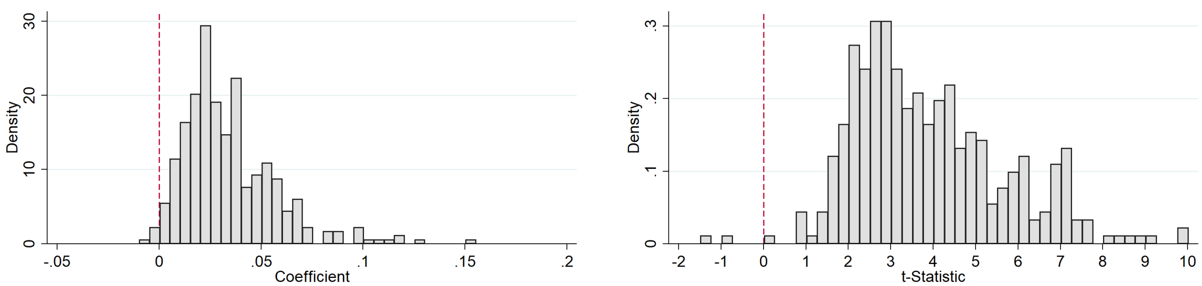


Figure 3. Variation across art units in examiners' self-citation rate.
This figure plots the distribution of estimated coefficients on the *Same examiner* indicator and associated t-statistics when re-estimating the model shown in column 4 of Table 2 separately for each art unit in our sample. Recall that in Table 2, we estimate OLS regressions within the sample of all pairwise combinations $\{i, k\}$ between any given patent i granted in art unit j in year t and all patents k granted in art unit j in years $t-5$ through $t-1$; the dependent variable is an indicator set equal to one if patent i has an examiner-added citation to patent k, and $1\{Same\ examiner\}$ is an indicator set equal to one if patents i and k were reviewed by the same examiner. Coefficients are scaled by a factor of 100 and t-statistics are based on standard errors clustered at the examiner level. Panel A reports the results for our full sample of art units, while Panel B focuses on art unit-years belonging to the random examiner assignment subsample, where within-art unit examiner technological specialization is not a concern; see Section 3.1.1 for details on how this subsample is defined.

Table 1. Summary statistics

Panel A: Art unit-year statistics

	N	mean	sd	p25	p50	p75
Patents	10,236	317	252	112	299	464
Examiners	10,236	14.2	10.5	10	14	17

Panel B: Patent citation statistics

	N	mean	sd	p25	p50	p75
No. citations	4,242,287	17.52	56.25	3	16	14
No. examiner-added citations	4,242,287	4.034	5.20	1	3	5

Panel C: Startup patent acquisition statistics

	N	mean	sd	p25	p50	p75
1{Is acquired}	69,326	23.3	42.3	0	0	0

Panel D: Inventor statistics

	N	mean	sd	p25	p50	p75
No. future patents	147,681	2.85	5.48	0	1	3
No. prior patents	147,681	3.19	7.45	0	0	3

This table reports key summary statistics for our sample. Panel A shows statistics on the number of patents and examiners for each art unit-year. Panel B shows citation statistics for the startup patents in our sample, while Panel C describes how often these patents are acquired within five years of being granted. Panel D describes the patenting output of the inventors at the startups in our sample. Specifically, for each startup, we consider all individuals who are listed as an inventor in one of the startup's first five patents as long as the patent's grant date is within one year of the startup's first patent grant. We report statistics on the number of patents granted to each inventor within five years of the granting of their first patent at the startup as well as on the patents granted to each inventor prior to joining the startup.

Table 2. Are examiners more likely to cite patents they reviewed in the past?

	Dep. var.: Does the current patent have an examiner-added citation to the prior patent?				
	(1)	(2)	(3)	(4)	(5)
Panel A: Full 1% random sample					
1{Same examiner}	0.050***	0.050***	0.050***	0.041***	0.040***
	(4.33)	(4.24)	(4.22)	(4.60)	(4.49)
Fixed effects:					
Art unit × Prior year	Y	Y	N	N	N
Current patent	N	Y	N	N	N
Current patent × Prior year	N	N	Y	Y	Y
(Current × Prior) tech. group	N	N	N	Y	× Prior year
N obs.	142,187,358	142,186,563	142,182,165	142,162,470	142,046,575
Adj. R^2	0.000	0.001	0.002	0.004	0.008
Panel B: Random examiner assignment subsample					
1{Same examiner}	0.045***	0.044***	0.044***	0.036***	0.035***
	(5.34)	(5.22)	(5.23)	(6.11)	(5.98)
Fixed effects:					
Art unit × Prior year	Y	Y	N	N	N
Current patent	N	Y	N	N	N
Current patent × Prior year	N	N	Y	Y	Y
(Current × Prior) tech. group	N	N	N	Y	× Prior year
N obs.	82,193,504	82,192,297	82,188,230	82,174,072	82,106,067
Adj. R^2	0.000	0.001	0.002	0.004	0.008

This table examines whether a patent is more likely to have an examiner-added citation to a patent recently granted in the same art unit that was reviewed by the same examiner than to an otherwise similar patent that was reviewed by another examiner. To test this, for any patent i granted in art unit j in year t ("current" patents), we form all pairwise combinations between i and all patents k granted in art unit j in years $t-5$ through $t-1$ ("prior" patents). We then estimate OLS regressions within the sample of all pairwise combinations $\{i, k\}$, where the dependent variable is an indicator set equal to one if patent i has an examiner-added citation to patent k. The key independent variable, $1\{\textit{Same examiner}\}$, is an indicator set equal to one if patents i and k were reviewed by the same examiner. Given the shear number of pairwise combinations $\{i, k\}$ possible, for tractability we randomly draw a 1% sample from our full sample of art unit-years and consider only current patents i from this random sample—as well as the full set of pairwise combinations $\{i, k\}$ involving each current patent i from the 1% sample. Panel A shows results for this 1% random sample. Panel B focuses only on those art unit-years within the 1% random sample that belong to the random examiner assignment subsample, where within-art unit examiner technological specialization is not a concern, in years $t-5$ through t; see Section 3.1.1 for details on how this subsample is defined. Coefficients are scaled by a factor of 100. t-statistics (shown in brackets) are based on standard errors clustered at the art unit level. ***, **, and * denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Table 3. Are examiner-added citations associated with more startup patent acquisitions?

	Dep. var.: Startup's first patent acquired by incumbent?				
	(1)	(2)	(3)	(4)	(5)
Panel A: Full sample					
1{Examiner-added cite to startup}	1.440***	1.430***	1.376***	1.345***	1.304***
	(13.01)	(12.83)	(11.78)	(11.20)	(10.33)
Fixed effects:					
Incumbent firm	Y	N	N	N	N
Startup patent Art unit × Year	Y	Y	N	N	N
Incumbent firm × Year	N	Y	× Art	× Art	× Art
Incumbent firm × Tech. group	N	N	N	Y	× Year
N obs.	29,615,297	29,596,720	29,499,060	27,354,436	23,137,188
Adj. R^2	0.005	0.018	0.099	0.132	0.206
Panel B: Random examiner assignment subsample					
1{Examiner-added cite to startup}	1.131***	1.127***	1.057***	1.009***	0.924***
	(10.28)	(10.10)	(8.73)	(8.18)	(7.29)
Fixed effects:					
Incumbent firm	Y	N	N	N	N
Startup patent Art unit × Year	Y	Y	N	N	N
Incumbent firm × Year	N	Y	× Art	× Art	× Art
Incumbent firm × Tech. group	N	N	N	Y	× Year
N obs.	13,876,193	13,856,477	13,787,665	12,548,310	10,373,274
Adj. R^2	0.006	0.023	0.106	0.146	0.213

This table examines whether incumbent firms that have been asked by an examiner to cite a startup's first patent are more likely to go on to acquire that patent. The table shows the results of estimating OLS regressions within the sample of all pairwise combinations between a startup's first patent and its potential acquirers. The dependent variable is an indicator set equal to one if the potential acquirer does indeed acquire the startup patent within five years of its grant date. The key independent variable, 1{*Examiner-added cite to startup*}, is an indicator set equal to one if at least one of the patents granted to the potential acquirer within five years of the startup patent's grant date has an examiner-added citation to the startup patent. For every startup's first patent, we define its set of potential acquirers as any firm that had been granted a patent in the same art unit that reviewed the startup patent within the five years prior to the startup patent's grant date. Panel A shows results for the full sample of startup first patents. Panel B focuses only on startup first patents granted in art unit-years that belong to the random examiner assignment subsample, where within-art unit examiner technological specialization is not a concern, during both the startup patent grant year and the following five years; see Section 3.1.1 for details on how this subsample is defined. Coefficients are scaled by a factor of 100. t-statistics (shown in brackets) are based on standard errors clustered at the art unit level. ***, **, and * denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Table 4. Does sharing examiner with an incumbent increase the likelihood that a startup patent is acquired?

	Dep. var.: Startup's first patent acquired by incumbent?									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Full Sample										
1{Same examiner}	0.052***	0.051***	0.030***	0.027***	0.027***	0.037***	0.036***	0.026***	0.023***	0.023***
	(17.29)	(16.95)	(12.62)	(10.40)	(8.35)	(14.61)	(14.45)	(10.89)	(8.73)	(7.22)
... × 1{Frequent acquirer}						0.056***	0.056***	0.019***	0.016**	0.014*
						(7.73)	(7.50)	(2.93)	(2.32)	(1.67)
Fixed effects:										
Incumbent firm	Y	N	N	N	N	Y	N	N	N	N
Art unit × Year	Y	Y	N	N	N	Y	Y	N	N	N
Incumbent × Year	N	Y	× Art	× Art	× Art	N	Y	× Art	× Art	× Art
Incumbent × Tech. grp	N	N	N	Y	× Year	N	N	N	Y	× Year
N obs.	29,615,297	29,596,720	29,499,060	27,354,436	23,137,188	29,615,297	29,596,720	29,499,060	27,354,436	23,137,188
Adj. R^2	0.004	0.017	0.098	0.131	0.205	0.004	0.017	0.098	0.131	0.205
Panel B: Random examiner assignment sample										
1{Same examiner}	0.082***	0.082***	0.042***	0.037***	0.040***	0.036***	0.036***	0.031***	0.026***	0.028***
	(10.78)	(10.47)	(6.84)	(5.40)	(4.44)	(8.72)	(8.61)	(7.23)	(5.72)	(4.62)
... × 1{Frequent acquirer}						0.099***	0.097***	0.025**	0.024*	0.025
						(7.69)	(7.37)	(2.00)	(1.76)	(1.44)
N obs.	13,876,193	13,856,477	13,787,665	12,548,310	10,373,274	13,876,193	13,856,477	13,787,665	12,548,310	10,373,274
Adj. R^2	0.009	0.019	0.113	0.141	0.206	0.009	0.019	0.113	0.141	0.206

This table examines whether incumbent firms that share a patent examiner with a startup's first patent are more likely to go on to acquire that patent. The table shows the results of estimating OLS regressions within the sample of all pairwise combinations between a startup's first patent and its potential acquirers. The dependent variable is an indicator set equal to one if the potential acquirer does indeed acquire the startup's first patent within five years of its grant date. The table differs from Table 3 in that here the key independent variable, $1\{Same\ examiner\}$, is an indicator set equal to one if at least one of the patents granted to the potential acquirer within five years of the startup patent's grant date was reviewed by the same examiner as the startup patent. For every startup's first patent, we again define its set of potential acquirers as any firm that had been granted a patent in the same art unit that reviewed the startup patent within the five years prior to the startup patent's grant date. In columns 6 through 10, we augment each of the models in columns 1 through 5 by interacting the $1\{Same\ examiner\}$ indicator with a $1\{Frequent\ acquirer\}$ indicator that is equal to one if the incumbent firm has acquired at least 10 patents over the previous five years (the uninteracted $1\{Frequent\ acquirer\}$ indicator is subsumed by the incumbent firm fixed effects). Panel A shows results for the full sample of startup first patents. Panel B focuses only on startup first patents granted in art unit-years that belong to the random examiner assignment subsample, where within-art unit examiner technological specialization is not a concern, during both the startup patent grant year and the following five years; see Section 3.1.1 for definition details. Panel B contains the same fixed effects as Panel A (not listed for brevity). Coefficients are scaled by a factor of 100. t-statistics (shown in brackets) are based on standard errors clustered at the art unit level. ***, **, and * denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Table 5. First-stage: Linkages to incumbents via shared examiners as source of exogenous variation in startup patent acquisitions

	Dep. var.: Startup's first patent acquired by incumbent?					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full sample						
N linked incumbents	1.981***	1.860***	1.937***			
	(7.09)	(6.66)	(6.45)			
Log(1+N linked incumbents)				1.885***	1.772***	1.839***
				(7.60)	(7.34)	(7.19)
Fixed effects:						
Startup pat. Art unit × Year	Y	Y	Y	Y	Y	Y
Startup pat. Tech. group	N	Y	× Year	N	Y	× Year
N obs.	68,752	68,731	67,099	68,752	68,731	67,099
Adj. R^2	0.113	0.122	0.186	0.113	0.122	0.186
Panel B: Random examiner assignment subsample						
N linked incumbents	1.779***	1.701***	1.743***			
	(4.84)	(4.66)	(4.28)			
Log(1+N linked incumbents)				1.541***	1.452***	1.470***
				(4.41)	(4.37)	(4.04)
Fixed effects:						
Startup pat. Art unit × Year	Y	Y	Y	Y	Y	Y
Startup pat. Tech. group	N	Y	× Year	N	Y	× Year
N obs.	33,603	33,563	32,006	33,603	33,563	32,006
Adj. R^2	0.137	0.153	0.225	0.137	0.153	0.225

This table examines whether startups whose first patent is linked to more acquisition-active incumbents via shared patent examiners are more likely to have that first patent acquired. The table shows the results of estimating OLS regressions where the dependent variable is an indicator set equal to one if a startup has its first patent acquired within five years of its granting. The key independent variable, *N linked incumbents*, counts the number of linkages via shared patent examiners that each startup in our sample has to acquisition-active incumbents with a history of patenting in the same art unit where the startup's first patent was granted; see Section 4.2 for details on how this variable is defined. Panel A shows results for the full sample of startups. Panel B focuses only on startups whose first patent was granted in art unit-years belonging to the random examiner assignment subsample, where within-art unit examiner technological specialization is not a concern, during both that first patent's grant year and the following five years; see Section 3.1.1 for details on how this subsample is defined. Coefficients are scaled by a factor of 100. t-statistics (shown in brackets) are based on standard errors clustered at the art unit level. ***, **, and * denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Table 6. Do startup patent acquisitions affect an inventor's future patenting quantity? OLS results

Dep. var.:	No. future patents		Any future patents?		Log(no. future patents) if at least one	
	(1)	(2)	(3)	(4)	(5)	(6)
1{Startup patent acquired}	0.403***	0.165***	0.055***	0.041***	0.069***	0.043***
	(7.14)	(3.24)	(11.90)	(9.38)	(5.36)	(3.55)
Log(1+prior no. patents)		2.091***		0.121***		0.329***
		(50.69)		(62.29)		(65.56)
Fixed effects:						
Startup pat. Art unit × Year	Y	Y	Y	Y	Y	Y
Startup pat. Tech. group × Year	Y	Y	Y	Y	Y	Y
N obs.	147,681	147,681	147,681	147,681	83,628	83,628
Adj. R^2	0.133	0.271	0.133	0.190	0.150	0.275

This table examines how the acquisition of a startup inventor's first patent affects the inventor's future patenting quantity. The table shows the results of estimating OLS regressions where the dependent variable measures the inventor's patenting quantity during the five years following the granting of her first patent while working at the startup. Specifically, in columns 1-2, the dependent variable is the (1%-winsorized) number of patents granted to the inventor during these five years. In columns 3-4, the dependent variable is an indicator set equal to one if the inventor is granted at least one patent during the same five years. In columns 5-6, the dependent variable is the logarithm of the number of patents granted to the inventor also within five years; thus, in columns 5-6, we restrict our analysis to inventors that are granted at least one future patent. The key independent variable, 1{*Startup patent acquired*}, is an indicator set equal to one if the inventor's first patent while working at that startup is acquired. In columns 2, 4, and 6, we control for the number of patents granted to the inventor prior to joining the startup. Our sample includes all individuals who are listed as an inventor in one of a startup's first five patents as long as the patent's grant date is within one year of the startup's first patent grant. In the case of inventors patenting at more than one startup, we only include subsequent patents if at least three years have elapsed since their first patent at their prior startup. t-statistics (shown in brackets) are based on standard errors clustered at the art unit level. ***, **, and * denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Table 7. Do startup patent acquisitions affect an inventor's future patenting quantity? IV results

Dep. var.:	No. future patents		Any future patents?		Log(no. future patents) if at least one	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full sample						
1{Startup patent acquired}	-4.360**	-6.658***	-0.030	-0.159	-0.865**	-1.196***
	(-2.07)	(-3.12)	(-0.20)	(-1.04)	(-2.34)	(-3.30)
Log(1+prior no. patents)		2.225***		0.125***		0.343***
		(37.15)		(35.22)		(48.60)
Fixed effects:						
Startup pat. Art unit × Year	Y	Y	Y	Y	Y	Y
Startup pat. Tech. group × Year	Y	Y	Y	Y	Y	Y
N obs.	147,681	147,681	147,681	147,681	83,628	83,628
First stage *F* statistic	22.1	21.6	22.1	21.6	28.0	27.7
Panel B: Random examiner assignment sample						
1{Startup patent acquired}	-10.115**	-13.383***	0.165	0.007	-2.097***	-2.494***
	(-2.46)	(-2.96)	(0.65)	(0.03)	(-2.63)	(-3.03)
Log(1+prior no. patents)		2.575***		0.124***		0.383***
		(20.03)		(20.43)		(23.21)
Fixed effects:						
Startup pat. Art unit × Year	Y	Y	Y	Y	Y	Y
Startup pat. Tech. group × Year	Y	Y	Y	Y	Y	Y
N obs.	71,062	71,062	71,062	71,062	39,965	39,965
First stage *F* statistic	13.5	12.7	13.5	12.7	12.9	12.5

This table examines how the acquisition of a startup inventor's first patent affects the inventor's future patenting quantity. The table shows the results of estimating 2SLS regressions where the dependent variable measures the inventor's patenting quantity during the five years following the granting of her first patent while working at the startup. The dependent variables are defined exactly as in Table 6. The key independent variable, 1{*Startup patent acquired*}, is an indicator set equal to one if the inventor's first patent while working at that startup is acquired. In the first stage, 1{*Startup patent acquired*} is instrumented with the *N linked incumbents* (defined as in Table 5). In columns 2, 4, and 6, we control for the number of patents granted to the inventor prior to joining the startup. For each second-stage model, the table also shows the respective first-stage Kleibergen-Paap *rk* Wald *F* statistic. Our sample includes all individuals who are listed as an inventor in one of a startup's first five patents as long as the patent's grant date is within one year of the startup's first patent grant. Panel A shows results for the full sample of startup inventors. Panel B focuses only on startup inventors patenting in art unit-years belonging to the random examiner assignment subsample, where within-art unit examiner technological specialization is not a concern; see Section 3.1.1 for details on how this subsample is defined. In the case of inventors patenting at more than one startup, we only include subsequent patents if at least three years have elapsed since their first patent at their prior startup. t-statistics (shown in brackets) are based on standard errors clustered at the art unit level. ***, **, and * denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Table 8. Do startup patent acquisitions affect an inventor's future patenting quality? OLS results

Dep. var.:	No. cites (1)	Log(cites) (2)	No. top 10%-cited patents (3)	No. top 5%-cited patents (4)	Avg. pat. > avg. quality? (5)	Log(cites per patent) (6)
1{Startup patent acquired}	0.422***	0.099***	0.063***	0.037***	0.031***	0.058***
	(3.00)	(4.09)	(3.28)	(2.87)	(4.57)	(3.22)
Log(1+prior no. patents)	3.273***	0.380***	0.442***	0.250***	0.030***	0.060***
	(38.27)	(42.17)	(37.23)	(32.52)	(14.26)	(10.19)
Fixed effects:						
Startup pat. Art unit × Year	Y	Y	Y	Y	Y	Y
Startup pat. Tech. group × Year	Y	Y	Y	Y	Y	Y
N obs.	147,681	74,114	147,681	147,681	83,432	74,114
Adj. R^2	0.174	0.217	0.171	0.154	0.140	0.152

This table examines how the acquisition of a startup inventor's first patent affects the inventor's future patenting quality. The table shows the results of estimating OLS regressions where the dependent variable measures the inventor's patenting quality during the five years following the granting of her first patent while working at the startup. Specifically, in column 1, the dependent variable is the (1%-winsorized) number of scaled citations received by the patents granted to the inventor during these five years; throughout the table, each patent's citation count is scaled by dividing it by the average number of citations received by patents granted in the same CPC technology group and year. In column 2, the dependent variable is the logarithm of the number of scaled citations received by the patents granted to the inventor during the same five years; thus, in columns 2, we restrict our analysis to inventors that are granted at least one future patent and at least one of these patents receives one citation. In columns 3-4, the dependent variable is the (1%-winsorized) number of top-cited patents granted to the inventor within five years; we define a patent as a top-cited patent if the number of citations it receives is in the top 10% (in column 3) or the top 5% (in column 4) of citations received by patents granted in the same CPC technology group and year. In columns 5, the dependent variable is an indicator set equal to one if the average number of scaled citations per patent received by the patents granted to the inventor within five years is greater than one; thus, this indicator identifies whether the average patent granted to the inventor within five years has more citations than the average number of citations received by patents granted in the same CPC technology group and year. To be included in column 5, an inventor needs to have been granted at least one future patent. In column 6, the dependent variable is the logarithm of the average number of scaled citations per patent received by the patents granted to the inventor within five years; to be included in column 6, an inventor needs to have been granted at least one future patent and at least one of these patents needs to have received one citation. The key independent variable, 1{*Startup patent acquired*}, is an indicator set equal to one if the inventor's first patent while working at that startup is acquired. In all columns, we control for the number of patents granted to the inventor prior to joining the startup. Our sample includes all individuals who are listed as an inventor in one of a startup's first five patents as long as the patent's grant date is within one year of the startup's first patent grant. In the case of inventors patenting at more than one startup, we only include subsequent patents if at least three years have elapsed since their first patent at their prior startup. t-statistics (shown in brackets) are based on standard errors clustered at the art unit level. ***, **, and * denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Table 9. Do startup patent acquisitions affect an inventor's future patenting quality? IV results

Dep. var.:	No. cites	Log(cites)	No. top 10%-cited patents	No. top 5%-cited patents	Avg. pat. > avg. quality?	Log(cites per patent)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full sample						
1{Startup patent acquired}	-11.950**	-1.999***	-1.804**	-0.953**	-0.239	-0.771*
	(-2.26)	(-2.81)	(-2.48)	(-2.09)	(-1.53)	(-1.75)
Log(1+prior no. patents)	3.515***	0.402***	0.479***	0.269***	0.033***	0.069***
	(26.34)	(33.40)	(25.38)	(22.74)	(12.77)	(9.37)
Fixed effects:						
Startup pat. Art unit × Year	Y	Y	Y	Y	Y	Y
Startup pat. Tech. group × Year	Y	Y	Y	Y	Y	Y
N obs.	147,681	74,114	147,681	147,681	83,432	74,114
First stage *F* statistic	21.6	20.3	21.6	21.6	27.5	20.3
Panel B: Random examiner assignment sample						
1{Startup patent acquired}	-23.677**	-3.413**	-3.469**	-1.816**	-0.545*	-1.182
	(-2.22)	(-2.48)	(-2.41)	(-2.05)	(-1.75)	(-1.41)
Log(1+prior no. patents)	4.021***	0.430***	0.543***	0.305***	0.033***	0.063***
	(14.08)	(17.68)	(13.71)	(12.26)	(6.15)	(4.37)
Fixed effects:						
Startup pat. Art unit × Year	Y	Y	Y	Y	Y	Y
Startup pat. Tech. group × Year	Y	Y	Y	Y	Y	Y
N obs.	71,062	35,974	71,062	71,062	39,877	35,974
First stage *F* statistic	12.7	11.0	12.7	12.7	12.8	11.0

This table examines how the acquisition of a startup inventor's first patent affects the inventor's future patenting quality. The table shows the results of estimating 2SLS regressions where the dependent variable measures the inventor's patenting quality during the five years following the granting of her first patent while working at the startup. The dependent variables are defined exactly as in Table 8. The key independent variable, 1{*Startup patent acquired*}, is an indicator set equal to one if the inventor's first patent while working at that startup is acquired. In the first stage, 1{*Startup patent acquired*} is instrumented with the *N linked incumbents* (defined as in Table 5). In all columns, we control for the number of patents granted to the inventor prior to joining the startup. For each second-stage model, the table also shows the respective first-stage Kleibergen-Paap *rk* Wald *F* statistic. Our sample includes all individuals who are listed as an inventor in one of a startup's first five patents as long as the patent's grant date is within one year of the startup's first patent grant. Panel A shows results for the full sample of startup inventors. Panel B focuses only on startup inventors patenting in art unit-years belonging to the random examiner assignment subsample, where within-art unit examiner technological specialization is not a concern; see Section 3.1.1 for details on how this subsample is defined. In the case of inventors patenting at more than one startup, we only include subsequent patents if at least three years have elapsed since their first patent at their prior startup. *t*-statistics (shown in brackets) are based on standard errors clustered at the art unit level. ***, **, and * denote significance at the 1%, 5%, and 10% level (two-sided), respectively.