

Heterogeneity in Knowledge Flows of Regions: Impact on Invention Quality

Abstract

Using patent citations as measures of knowledge flows, we explore if the different types of knowledge flows in a region affect the quality of inventions originating in that region. We leverage a database of worldwide urban centers obtained from remote sensing data and find that local knowledge flows do not seem to impact the inventive quality of regions. However, knowledge flows within the firm across regions seem to have a positive effect on invention quality.

Introduction

Scholars of economics and strategy have for long recognized that clusters and agglomeration economies play an important role in fostering innovation (Marshall, 2009; Porter, 1990). Agglomeration economies arise due to labor pooling advantages, economies of specialization of local suppliers, and knowledge spillovers (Krugman, 1991; Porter, 1990). In this study, we examine how the nature of knowledge spillovers or flows in a region affect the quality of the inventions generated in the region.

Several studies have used patent citations to demonstrate that knowledge flows are localized (Alcácer and Gittelman, 2006; Almeida and Kogut, 1999; Jaffe et al., 1993). Regions, however vary in their inventive output (Agrawal et al., 2014) and the nature of knowledge flows in a region may be one source of this variation within regions. In this study we use citation data of patents applied for between 2001 and 2012 to empirically estimate the relationship between knowledge flows of a region and quality of inventions from that region.

The rest of the paper is organized as follows. The next section defines a framework to classify knowledge flows in a region and motivates our work by demonstrating how different regions fare differently in terms of knowledge flows. We then describe our data and methods in the following section. Our preliminary results are then presented, followed by a discussion of the results. We conclude with next steps and open questions for further research.

Effects of knowledge flows on quality of inventions

We categorize all knowledge flows incorporated into an invention along two dimensions: first, whether the knowledge flows among inventors are local to a geographical region or not, and second, whether knowledge flows are within the boundary of the firm or not. This classification allows us to analyze knowledge flows in four mutually exclusive, but collectively exhaustive categories as illustrated in Figure 1. We next describe each quadrant and discuss how the category of knowledge flow in that quadrant can affect invention quality. Within the context of this framework, we ask what is the net effect of each category of knowledge flow on invention quality, and which category of flow has the largest effect on invention quality.

| | Same Region | Different Region |
|--------------------|-----------------------------|----------------------------|
| Same Assignee | Independent Research Center | Geographic Diversification |
| Different Assignee | Cluster | Diffusion |

Figure 1: Categories of knowledge flows

The top left quadrant, labelled an "Independent Research Center" captures those knowledge flows that reflect competence building. Since these knowledge flows are both within the region and within the firm, these flows represent local search on two dimensions (within firm and within region). Thus, while the competence that is being built up by the Independent Research Center can be expected to have a positive effect on invention quality, the localness of the search on both dimensions may have a negative effect on invention quality. Figure 2 depicts the knowledge flows for this category (percentage of backward citations from this region that are to the same firm or assignee and same region) across time for five regions: Bangalore, Beijing, Tel Aviv-Yafo, Boston and San Jose (core of "Silicon Valley"). While our empirical analysis covers all the major regions of the world, we chose these five regions as illustrative examples. We note that both San Jose and Boston report a higher proportion of knowledge flows within the same firm in the same region, while Bangalore and Tel Aviv-Yafo have the lowest proportion (fewer than 1%) of their citations from the same firm within the same region.

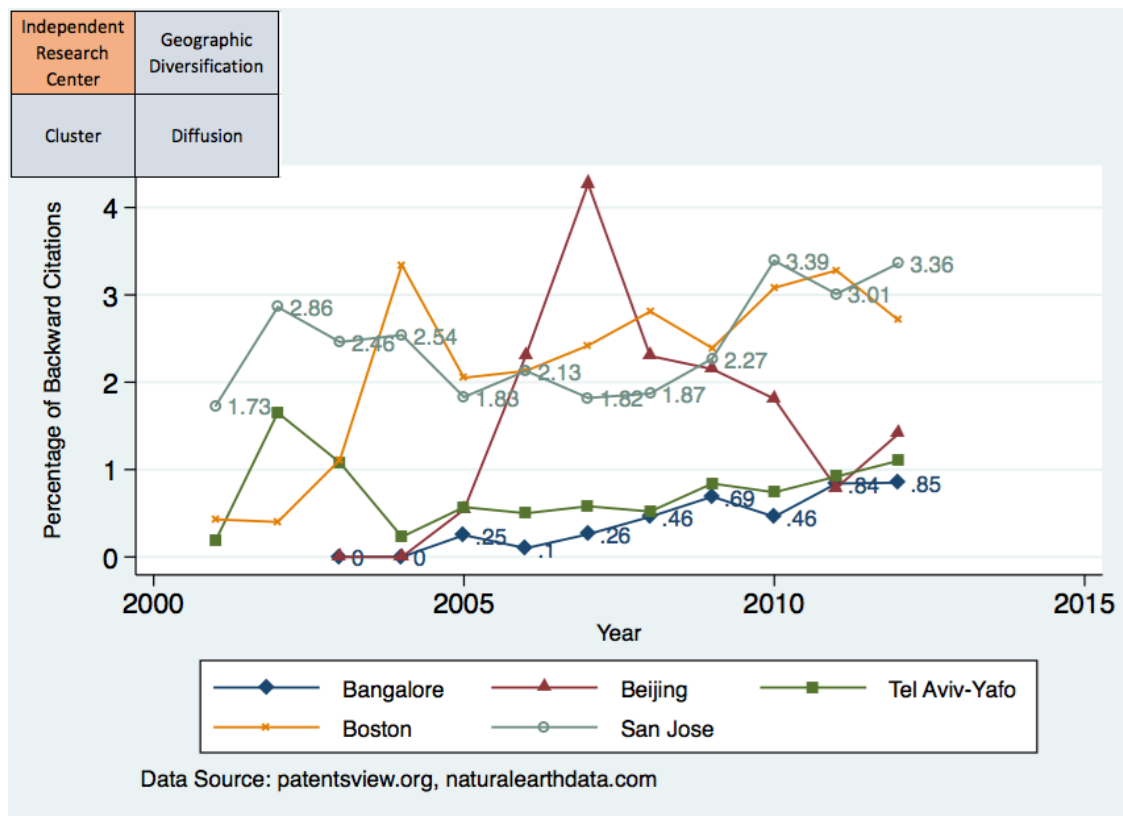


Figure 2: Knowledge flows within regions and within assignees

The quadrant on the bottom left, labelled "Cluster" captures knowledge spillovers within a region. Here firms may be seen as performing local search on one dimension (within regions) but not the other (within firms). Figure 3 depicts the knowledge flows for this category across time for the same five regions. San Jose clearly stands out from the rest, suggesting a higher amount of across firm flows of knowledge in Silicon Valley, a result consistent with several prior studies.

The quadrant on the top right, labelled as "Geographic Diversification" captures local search on the dimension of the firm (across geographies) but not across regions. Innovations that are built on knowledge from several regions can be expected to benefit from the diversity of knowledge across regions. Yet, as in the previous quadrant, there is localness along the dimension of firm and such localness can have a negative effect on invention quality (Rosenkopf and Nerkar, 2001). Figure 4 depicts the knowledge flows for this category across time for the five regions. We note that Bangalore and Beijing have a relatively higher proportion of knowledge flows from same assignees in different locations, thus confirming the role of these regions as R&D outposts of multinational firms.

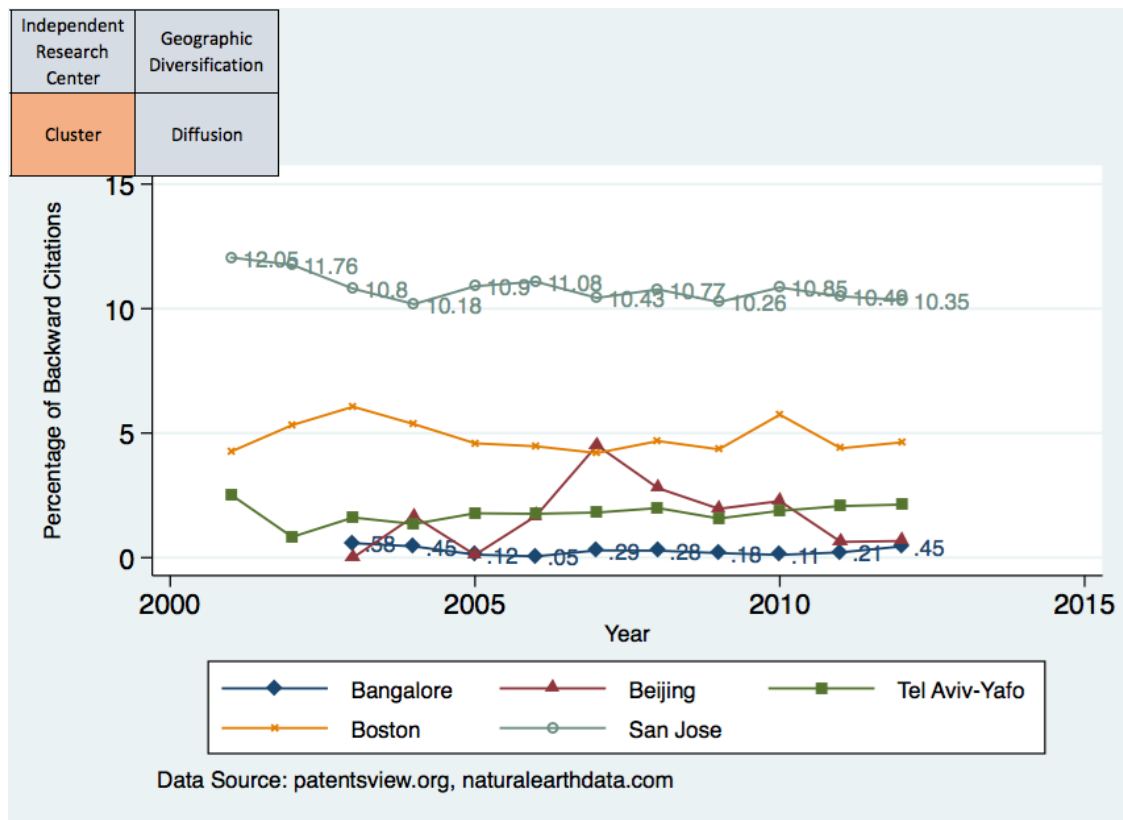


Figure 3: Knowledge flows within regions and across assignees

Finally, the bottom right quadrant labelled "Diffusion" captures high exploration along both dimensions, indicating the development of a global pipeline (Bathelt et al., 2004). Figure 5 depicts the knowledge flows for this category across time for the five regions. We note that Bangalore, Beijing and Tel Aviv-Yafo have a higher level of knowledge flows from other firms in other regions compared to Boston and San Jose, which is to be expected given that the absolute level of innovative activity in these emerging hotspots is still lower compared to that in Boston and San Jose.

As can be seen from the preceding discussion, prior theory suggests both positive and negative effects for each of these four categories of knowledge flows and it is not clear what the net effect will be on invention quality. This also suggests that prior theory does not provide guidance on which category of knowledge flows will have the highest effect on invention quality. Since theory does not provide us with an answer, we rely on empirical analysis to inform us on the net effect of each category of knowledge flow on invention quality and which category has the highest effect on invention quality.

Data and Measures

We use patent citations data from the U.S. Patent Office (USPTO) as provided by patentsview.org. The USPTO provides information on assignee, the location of inventors, and year of patent application. We use this information to identify which patents belong to which region in a given year. Since there can be more than one inventor on a patent, a patent can belong to more than one region. We compare the assignee and inventor location of each patent with each assignee and inventor of each backward citation to identify the category of knowledge flow (e.g., same assignee, different location) indicated by the backward citation. Additionally, to map location data of inventors from USPTO to regions, we use urban centers data for worldwide locations from Natural Earth Data that uses remote sensing data to determine urban agglomerations (a process developed in Schneider et al. (2003)). While it has been common practice to use Metropolitan Statistical Areas (MSA) for analyses related to economic geography in the U.S., an equivalent

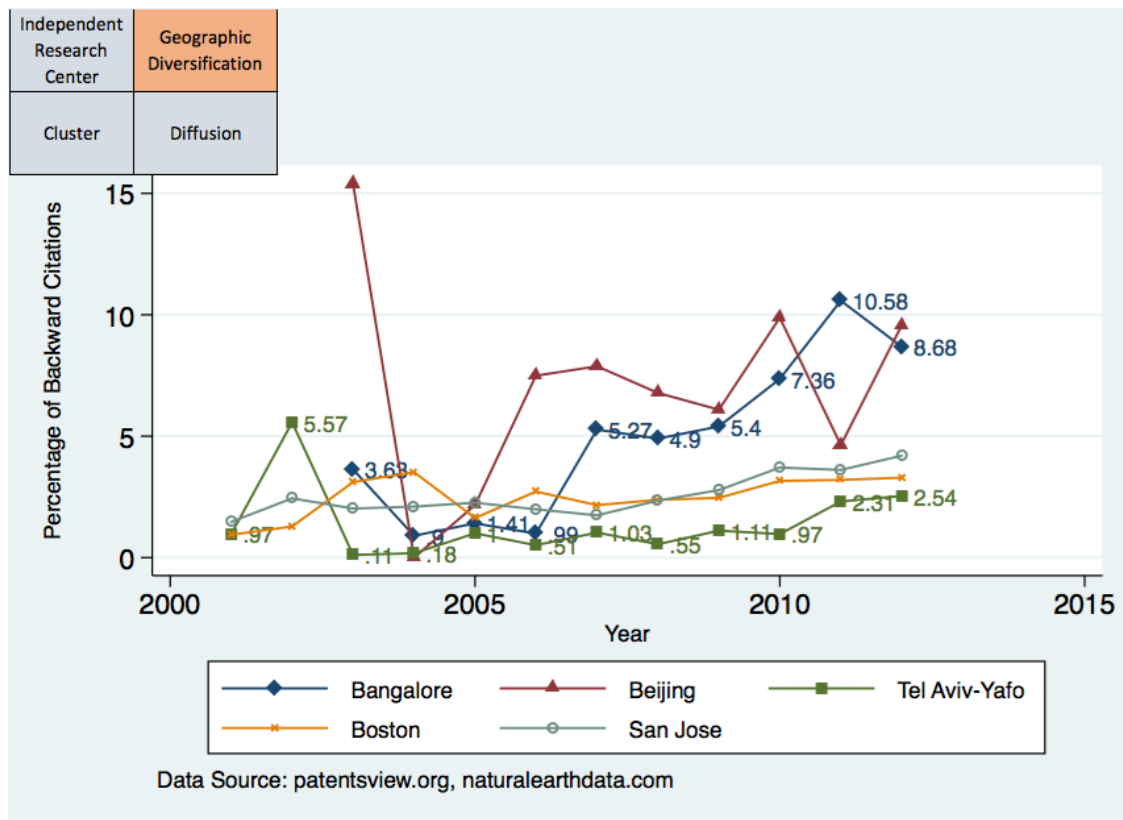


Figure 4: Knowledge flows across regions and within assignees

measure is unavailable for the rest of the world. For comparability and consistency, we choose to use the urban centers definitions from [Natural Earth Data](#) for all regions both within U.S. and outside U.S.

Our unit of analysis is the region-year. To be consistent with our objective of measuring knowledge flows, we restrict ourselves to those citations categorized as 'cited by applicant' and leave out those categorized as 'cited by examiner' because the latter may not represent knowledge flows. This decision has the additional effect of limiting our period of analysis to citing patents applied for after the year 2000 since the data on which citations were added by examiners is available for patents from only 2001 onwards. We restrict our sample to patents applied for between 2001 - 2012, but citations received till 2015.

Our primary dependent variable is the total count of citations received (till 2015) by patents belonging to a region-year. For robustness, we also report results for total non-self citations received as the dependent variable. Our independent variables are the percentage of backward citations made to each of the four categories in our defined framework: those to a) same region, same assignee, b) same region, different assignee, c) different region, same assignee, and d) different region, same assignee.

We control for the total number of citations made in the region-year, the total number of patents in the region-year, the size of the patent pool in the region-year, as well as the percentage of patents in region-year in each technology subcategory as defined by [Hall et al. \(2001\)](#). The patent pool is the total number of patents that belong to a region up to the previous year. It is important to control for the size of the patent pool as regions that have a larger patent pool (such as San Jose) will have more patents that can be cited and can therefore have larger within region spillovers as compared to a region that has only a small patent pool. We include region fixed effects and year dummies in all regression models so as to control for region level and year specific effects, if any. Since our dependent variable is a count variable, we used negative binomial regression analysis with fixed effects.

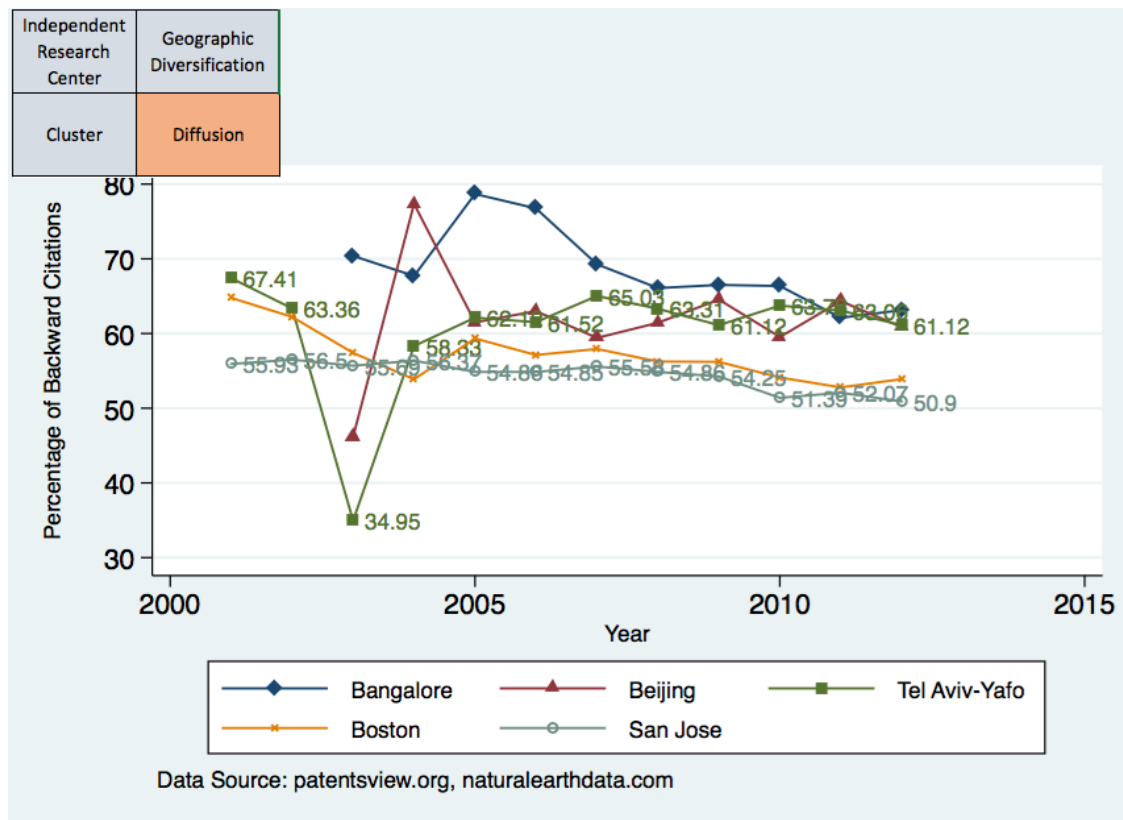


Figure 5: Knowledge flows across regions and across assignees

Results

The preliminary results from our analysis are presented in Table 1. Model 1 reports the results for all regions worldwide, while Model 2 and Model 3 report results for U.S. locations and non-U.S. locations respectively. Across the three models we find that local knowledge flows within the firm do not seem to have a significant impact on the quality of inventions as measured by the number of citations received. This result is robust to using non-self citations as the dependent variable as presented in Table 2.

Our preliminary findings in Table 1 suggest no evidence that local knowledge spillovers (i.e., same region, different assignee) lead to higher quality inventions. One possible explanation for the lack of evidence for local knowledge spillovers may be to suggest U.S. specific effects. However as the results in model 2 of Table 1 suggest, the trend is confirmed in a U.S.-only sample. It seems therefore that the implication for the lack of effect of localized knowledge flows on invention quality is robust to regional or country sampling.

The effect of non-local knowledge flows however is less clear. While geographic diversification is seen to benefit all regions (Table 1), the effect is not statistically significant for non-U.S. locations (Table 2). This may suggest that there are regional, and potentially country effects that may be able to explain the phenomenon better. Finally, building on knowledge from outside the firm and outside the region does not seem to improve invention quality.

Limitations

While the use of patent citations as a measure of knowledge flows has been popular in the literature, this may nevertheless be subject to error (Arora et al., 2017). Our definition of regions is dependent on the latitude/longitude assignment

in the patentsview.org data and on the urban centers definition in the [Natural Earth Data](#). Any systematic biases in the definition of regions can create biases in measures of within region and across region knowledge flows.

Conclusion

While still at a preliminary stage, our analysis seem to suggest that local knowledge flows as measured by patent citations may not have a significant effect on the quality of inventions produced in a region. This casts a doubt on the widely accepted idea that local knowledge spillovers are an important source of agglomeration economies. A potential extension of the study could be to conduct empirical analysis at the level of firm-year rather than at the region-year. We could additionally look at the additional dimension of technology (within and outside technological domain, [Rosenkopf and Nerkar \(2001\)](#)) in addition to those of within/outside region and within/outside firm. This may provide us with a more nuanced understanding of the factors affecting invention quality. Future studies could potentially examine other measures of invention outcomes such as breakthrough inventions. Finally, while our work suggests that local knowledge spillovers do not affect invention quality, it is not quite as clear why this may be the case. We hope that our current work spurs further research in this direction.

References

- Agrawal, A., Cockburn, I., Galasso, A., and Oettl, A. (2014). Why are some regions more innovative than others? the role of small firms in the presence of large labs. *Journal of Urban Economics*, 81:149 – 165.
- Alcácer, J. and Gittelman, M. (2006). Patent citations as a measure of knowledge flows: The influence of examiner citations. *Review of Economics and Statistics*, 88(4):774–779.
- Almeida, P. and Kogut, B. (1999). Localization of knowledge and the mobility of engineers in regional networks. *Management Science*, 45(7):905–917.
- Arora, A., Belenzon, S., and Lee, H. (2017). Reversed citations and the localization of knowledge spillovers. Working Paper 23036, National Bureau of Economic Research.
- Bathelt, H., Malmberg, A., and Maskell, P. (2004). Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation. *Progress in Human Geography*, 28(1):31–56.
- Hall, B. H., Jaffe, A. B., and Trajtenberg, M. (2001). The nber patent citation data file: Lessons, insights and methodological tools. Working Paper 8498, National Bureau of Economic Research.
- Jaffe, A. B., Trajtenberg, M., and Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics*, 108(3):577–598.
- Krugman, P. R. (1991). *Geography and trade*. MIT press.
- Marshall, A. (2009). *Principles of Economics: Unabridged Eighth Edition*. Cosimo, Inc.
- Porter, M. E. (1990). *The Competitive Advantage of Nations*. Free Press New York.
- Rosenkopf, L. and Nerkar, A. (2001). Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal*, 22(4):287–306.
- Schneider, A., Friedl, M. A., McIver, D. K., and Woodcock, C. E. (2003). Mapping urban areas by fusing multiple sources of coarse resolution remotely sensed data. *Photogrammetric Engineering & Remote Sensing*, 69(12):1377–1386.

Table 1: Negative binomial regression analysis of invention quality (total citations received)

| | (1) Citations Received | (2) Citations Received | (3) Citations Received |
|--|------------------------------|------------------------------|------------------------------|
| Share Citations Made[Same Region, Same Assignee] | -0.169 (0.218) | -0.104 (0.623) | -0.134 (0.454) |
| Share Citations Made[Same Region, Different Assignee] | -0.149 (0.215) | -0.191 (0.458) | -0.0919 (0.468) |
| Share Citations Made[Different Region, Same Assignee] | 0.217 (0.012) | 0.266 (0.037) | 0.348 (0.004) |
| Share Citations Made[Different Region, Different Assignee] | 0.00828 (0.789) | 0.0315 (0.499) | 0.0179 (0.661) |
| Log (Total Citations Made) | 0.0180 (0.000) | 0.0198 (0.001) | 0.0134 (0.014) |
| Log (Num Patents) | 0.785 (0.000) | 0.811 (0.000) | 0.830 (0.000) |
| Log (Patent Pool Size) | -0.111 (0.000) | -0.227 (0.000) | -0.0944 (0.000) |
| Observations | 9241 | 3885 | 5356 |
| Groups | 1314 | 529 | 785 |
| Sample | All Locations | U.S. Locations | Non-U.S. Locations |

p-values in parentheses

All models include region fixed effects, year dummies and technology subcategory controls

Table 2: Negative binomial regression analysis of invention quality (non-self citations received)

| | (1) Non-Self Citations Received | (2) Non-Self Citations Received | (3) Non-Self Citations Received |
|--|--|--|--|
| Share Citations Made[Same Region, Same Assignee] | -0.232 (0.105) | -0.183 (0.392) | -0.316 (0.123) |
| Share Citations Made[Same Region, Different Assignee] | 0.0391 (0.733) | 0.0945 (0.721) | 0.0505 (0.699) |
| Share Citations Made[Different Region, Same Assignee] | 0.195 (0.035) | 0.263 (0.041) | 0.174 (0.212) |
| Share Citations Made[Different Region, Different Assignee] | 0.00989 (0.762) | 0.0203 (0.675) | 0.00983 (0.826) |
| Log (Total Citations Made) | 0.0150 (0.000) | 0.0139 (0.023) | 0.0107 (0.075) |
| Log (Num Patents) | 0.772 (0.000) | 0.795 (0.000) | 0.828 (0.000) |
| Log (Patent Pool Size) | -0.0453 (0.039) | -0.108 (0.006) | -0.0685 (0.017) |
| Observations | 8879 | 3732 | 5147 |
| Groups | 1199 | 478 | 721 |
| Sample | All Locations | U.S. Locations | Non-U.S. Locations |

p-values in parentheses

All models include region fixed effects, year dummies and technology subcategory controls