The Effect of Firm Interactions on Innovation

Connie Lee
Mines ParisTech
Cerna
connieleeeabc@gmail.com

Abstract
Firms interact in many ways. They compete for customers, they collaborate on research, they may have equity investments in each other, there may be employees moving between them, and they may buy each other's products. How these interactions then contribute to firm and industry innovation output is the question we try to address here.

1) Research Gap and State of the Art:
To the best of our knowledge, this question has surprisingly been very little studied. Econometricians working with firm level data like to assume independent observations. Furthermore, firm level data is often incomplete and subject to confidentiality issues. On the other hand, theorists in industrial organization begin their models by assuming a market structure with generally homogenous firm sizes and obtain few results on innovation output.

The endogenous growth and firm dynamics literature is perhaps the most relevant to us however it does not account for knowledge dynamics. Aghion et al (2005) describe an inverted U relationship between innovation and competition. Recently knowledge spillovers are included as an aggregate of all innovation in a given market in growth models (e.g. Dechezlepretre et al (2012)). However I posit that this measure confounds knowledge spillovers and competitiveness. Here I attempt to disentangle these two effects.

2) Theoretical arguments: In theory, the effect is particularly confounded because we expect more competition and more knowledge spillovers to both result in more innovation. When we segment by firm size, however, we expect competition to deter small and less competitive firms while larger firms should be more responsive.

Exogenous competitive shocks are rare though; most of the time we observe a time-invariant measure of competition by industry. As such, already competitive firms would expect to remain in their frontier position and will innovate less (since R&D is costly) as they get comfortable with their profits. Frontier firms nonetheless have the absorptive capacity (accumulated knowledge stock and research connections) to innovate and have been

3) Data description: Our measure of innovation is built from Patstat, a database on patent documents maintained by the European Patent Office. There are over 100 countries and regions covered and application filings go as far back as the mid 1800s. This database contains very comprehensive information on each patent application and is also what we use to identify firm collaborations, location spillovers, and firm technology competitiveness. In our robustness checks, we supplement this database with the Orbis database maintained by Bureau van Dijk. Orbis provides firm financial information and in particular allows us to distinguish between technology space and product space. It also allows us to define a measure of productivity and identify firm sizes based on sales and employment.

4) Empirical Analysis: Our baseline firm specification is a poisson regression on innovation output with measures of knowledge spillovers, firm competitiveness, and variables defining industry characteristics. We construct two knowledge spillover variables. One that is based on historical collaborators and one based on firm location. We also construct a measure of firm competitiveness defined as the knowledge stock gap between the given firm and the frontier firm in the industry. The industry variables also include a measure of competition (Herfindahl's index) and various moments of the industry – firm size distribution such as skewness. Our preliminary results indicate knowledge spillovers as the chief driver of innovation. We also provide evidence of an inverted U relationship with competition although it is highly skewed. However, the inverted U relationship no longer holds when there is a shock on industry competitiveness.

Jelcodes: O47
The Effect of Firm Interactions on Innovation

Connie Lee
Cerna, Mines ParisTech
connie.lee@mines-paristech.fr

December 2017

Preliminary

Abstract
Firms interact in many ways. They compete for customers, they collaborate on research, they may have equity investments in each other, there may be employees moving between them, and they may buy each other’s products. How these interactions then contribute to firm and industry innovation output and consequently productivity is the question we try to address here. I posit that it is important to take into account the combination of firm interactions. Here I will summarize the various strands of literature, document some empirical facts and hopefully elucidate some novel connections for economists working on this topic.

JEL classification: L11, O31, L22

Keywords: innovation, firm dynamics, competition
1 Introduction

Firms interact in many ways. They compete for customers, they collaborate on research, they may have equity investments in each other, there may be employees moving between them, and they may buy each other’s products. How these interactions then contribute to firm and industry innovation output and consequently productivity is the question we try to address here. We will go into detail on each of the above points, discuss the current state of the art and provide some accompanying empirical facts.

Aghion et al (2005)[1] describe an inverted U relationship between innovation and competition. They explain innovation incentives as based on the difference between post-innovation and pre-innovation rents of incumbent firms. Neck and neck sectors are endogenous and modelled with some level of collusion and thus positive rents, while unleveled sectors have a leader firm that gets the entire rent.

Also affecting the shape of this competition-innovation relationship is knowledge spillovers. In low competition sectors, there are fewer firms and they may be less likely to communicate on their current R&D work. Whereas more competitive sectors are likely to have firms that want their innovations to catch on and be validated so they are more likely to talk about and advertise their new technologies. The degree of advertising a firm does is unfortunately not a measure we can obtain empirically however.

When a firm first enters a market, it begins with one product on the market. If there is interest in the product the firm can either decide to innovate on this product in terms of better quality, lower marginal costs or accompanying products. At some point, the firm has survived long enough to recoup fixed costs and make a profit. As it continues to pile up cash, it may not feel the need to continue increasing investment in its current product lines. Instead of undertaking large fixed costs, it may decide to diversify its investments in other companies. [toeholds] This minimizes its risks and allows the firm to earn a financial income with potential for better buyout conditions in the future. As such, we would see a decrease in patenting from profitable firms
(and hence firms in sectors with low competition).

There is a burgeoning literature on firm heterogeneity usually measured by size of total sales or number of employees. There are a number of reduced form studies - see Gibrat (1911), Gabaix (2011)[6], Syverson (2011)[9], etc.

Manova et al (2017)[8] use firm input-output data from Belgium to study the sources of firm heterogeneity. They decompose firm heterogeneity into upstream, downstream, and buyer/supplier match quality as well as a measure for what they do not capture in the network which includes final demand and import export activity. They find that 81% of the firm size distribution is explained by the number of buyers downstream - this is different from final demand. Although their measure of size is total sales, this implies that innovation heterogeneity is largely explained by downstream demand as well. It is surprising that final demand plays such a small role and it highlights the vertical structure of firms' as a vital factor.

Carvalho and Draca (2017)[4] looks into the cascading effect of innovation along the supply chain. They study the case of Department of Defense procurement shocks on innovation in high-tech goods and services and essentially define a wider indirect market that gets cascading effects of a procurement decision. They find that the real impact on innovation is significantly higher than the isolated impact on one firm.

And that innovation decisions are central to understanding the drivers of firm heterogeneity.

The field of industrial organisation (IO) tries to isolate certain aspects and develop models to explain them. However to do so, they need to make very limiting assumptions. The field of endogenous growth makes even more simplifying assumptions on the behavior of firms and impose many reduced form generalizations. The empirical IO literature goes in the opposite direction and tries to capture as many details as possible but they are very limited by computing power.

Absorptive capacity is the concept that captures a firms’ ability to recognize valuable information and ideas and hence conduct research and produce innovations. This is frequently proxied by
R&D spending (Cohen and Levinthal 1990)[5].
To the best of our knowledge, the topic of firm interactions has been little studied empirically. Econometricians working with firm level data like to assume independent observations. Furthermore, firm level data is often incomplete and subject to confidentiality issues. On the other hand, theorists in industrial organization begin their models by assuming a market structure with generally homogenous firm sizes and obtain few results on innovation output. The endogenous growth and firm dynamics literature is perhaps the most relevant to us however it does not account for knowledge dynamics. Recently knowledge spillovers are included as an aggregate of all innovation in a given market in growth models (e.g. Dechezlepretre et al (2016)[2]). However I posit that this measure confounds knowledge spillovers and competitiveness. Empirical industrial organization also has similar goals however the field has taken a structural approach and needs to make assumptions on functional forms. There are also many computational limitations in estimating the structural models. Here I will focus on disentangling the effects of competition and knowledge spillovers.

2 Theoretical arguments

In theory, the effect is particularly confounded because we expect more competition and more knowledge spillovers to both result in more innovation. When we segment by firm size, however, we expect competition to deter small and less competitive firms while larger firms should be more responsive. Exogenous competitive shocks are rare though; most of the time we observe a time-invariant measure of competition by industry. As such, already competitive firms would expect to remain in their frontier position and will innovate less (since RD is costly) as they get comfortable with their profits. Frontier firms nonetheless have the absorptive capacity (accumulated knowledge stock and research connections) to innovate and have been observed to react more strongly to competitive shocks (e.g. import shocks in Melitz et al (2017)[3]).
3 Data description

Our measure of innovation is built from Patstat, a database on patent documents maintained by the European Patent Office. There are over 100 countries and regions covered and application filings go as far back as the mid 1800s. This database contains very comprehensive information on each patent application and is also what we use to identify firm collaborations, location spillovers, and firm technology competitiveness. In our robustness checks, we supplement this database with the Orbis database maintained by Bureau van Dijk. Orbis provides firm financial information and in particular allows us to distinguish between technology space and product space. It also allows us to define a measure of productivity and identify firm sizes based on sales and employment.

3.1 Patent Data

Our measure of innovation is built from PATSTAT (spring 2017 version), a database on patent documents maintained by the European Patent Office (EPO). There are over 100 countries and regions covered in the database with an application filing year going as far back as the mid 1800s. This database covers essentially the population of European patents and contains very comprehensive coverage of many other countries. Only about 2% of cited patent publication documents are missing.

PATSTAT has a very broad coverage of countries and is fairly well structured. However proper use of the database requires in depth knowledge of each country’s policies and idiosyncrasies as well as their changes over time.\footnote{For example, the Japan Patent Office imposes an additional fee on each claim after the first. Therefore on average, Japanese patents have a lower number of claims. Number of claims have been suggested as a patent quality indicator as they define the boundaries of the technology covered in the patent. However due to issues such as country specific rules, we will not use it as an indicator.} Information in the database consists of one table on patent application filings containing information on filing dates, authenticator office, number of applicants, number of inventors, patent family size, priority patent identifier if relevant, application type, corresponding publication id if relevant, granted status, etc.. There is similarly a table on patent publications including information on the patent authenticator, the publication kind,
the publication date, whether the publication was granted, the publication claims, and more. In addition, there is a table on people, either applicants or inventors, and their name, address details and estimated sectors. Finally, there are the tables that connect the applications and publications to people, the publications with other publications and application filings by citation, and the application filings to their priority filing. There are also smaller tables that add very specific information such as abstract texts, patent family citations, legal events, technology codes (IPC, CPC), product codes (NACE2), and some information on the non-patent literature collected through citations information.

There is a heavy legal literature on intellectual property rights however their use in economics is still fairly naive. One of the principle issues for use in economics is the measurement of patent quality. A naive first measure would be the count of the number of patents. However patents can consist of very different levels of innovative technology. There may be a discrepancy between countries as some countries are more lax in their innovativeness standards whereas other countries are more tough. This may, however, also change over time and also simply be different for the cross section of one country at one point in time. There have been many studies on patent quality but a consensus has not yet emerged. Historically, an indicator of quality were triadic patents (patents with applications in the United States, Europe and Japan), nowadays it is more common to include China and South Korea in this measure as well. However, either way, it is not the ideal measure for our purposes as it would over weigh our innovation measure towards those markets. Instead, a simple way to measure quality is to only count patents that have made applications in more than one country. This is both an indicator of quality as well as a good selection of technologies that are most affected by the timing of regulation implementation.

Since there can be substantial application, legal and possibly translation fees associated with each patent application, the decision to make a patent application must mean the expected payoff is higher than the costs.\footnote{Strategic use of patents, such as patent boxes and patent off-shoring for tax purposes, are becoming more and more common in recent years but arguably still a small part of the entire patent system. Here, we will assume only traditional use of patents.} Patents with applications in multiple countries are both an indicator of
high quality as well as an indicator that the applicants are connected with multiple markets. It is obvious that applicants with activity in more than one market are the most likely to be affected by the relative timing of regulations. We therefore expect this high quality indicator to be more reactive than a simple count of all patents.

Another common measure for patent quality is a value assigned based on backward citations. This implies that a patent cited ten times is worth more than a patent cited once. Jaffe and Trajtenberg (2017)[7] conduct a good survey of the current methods in this respect. One takeaway is that the citing patents should themselves have a value and that it should be taken into account when valuing the cited patent. The ideal method would be to take into account the entire history of citations however this is not tractable given our resources and therefore we use a second order measure where we multiply the citing patents’ value by a discount factor and add it to the nominal number of citations a patent has received. We still however have to interpret this measure with caution. Propensity to cite may have changed over time and different countries have different requirements for citations of prior art.

When creating a value of firm innovation we can further improve upon this measure by dividing by the number of patent applicants. Commonly done in the literature, this is a better measure of the value of a patent to the firm as the applicants will split the benefits of the patent. To do this we simply use the number of applicants calculated by PATSTAT. For the next step of our analysis we have to link patents to firms. Although PATSTAT provides a link between applicant and patent application, there is no structured procedure for noting applicant names. A single applicant may change the spelling of their name in different applications and in different patent offices. As such, simply using the PATSTAT applicant-patent application link table will result in much too many observations. There have been a number of attempts to harmonize the names in PATSTAT however they are subject to errors and although substantially cleaner, still encounter the same problem. To deal with this, we will use a firm-patent association dataset collected in Orbis. Orbis is maintained by Bureau Van Dijk and firms have a clear identifier with the associated patent application this also allows us to merge with the financial information of the firm.
We restrict our dataset to ≤ 2013 because there are substantial lags in data collection from different patent offices. All of the final countries in our regulatory dataset have some patent data up until 2015 however data completeness is not guaranteed and thus we use 2013 to leave a buffer. The buffer is also important in our quality measure built from citations. Studies have shown that most of a patent’s citations are made in the first five to seven years after publication however some continue to accumulate citations afterwards.

Patent applications can be filed in their respective national offices or in certain regional offices. The Patent Cooperation Treaty (PCT), signed in 1970, was designed to facilitate patent protection internationally. Similarly, Europe developed the European Patent Convention "to strengthen co-operation between the States of Europe in respect of the protection of inventions" in 1973. It established a system of law in Europe, for the 38 contracting states at the time, to allow a single procedure for the grant of patents that are ultimately subject to the same conditions as a national patent granted by that State.

In particular the EPO has an EP patent that can apply to all member states provided the applicant has paid the post grant fee in those states. PATSTAT also includes a legal event dataset that tracks changes made to a patent. In order to assign a country to each EP patent application, we use the legal event table to identify countries that received post grant fees. To be specific the legal event codes used were 'PGFP' (Post grant: annual fees paid to national office), 'AKX' (Payment of designated fees), 'AK' (Designated contracting states), and 'RBV' (Correction of designated states). If a patent application has an RBV correction, we use only those states. Many EP patents however, do not have payment fee information in the legal database however. This is particularly the case for patents that were not granted as there is then no reason to pay national fees. For the patents applications with no national information, we generate an estimate from the applicant history. To do so, we take the outer set of the countries listed in PGFP, AKX, and AK and we assign each country a fractional weight of \( \frac{1}{\text{number of patents per firm}} \) to get a firm distribution for each applicant. We then average these distributions over the set of applicants.
If the EP patent does not have any applicant information, we assign estimated designated states and a corresponding probability from the year average.

In order to identify sectors, we use the nace2 classification in Patstat. This is based on the IPC (International Patent Classification) technology codes listed in a patent application. Furthermore we follow Eurostat to categorize nace2 codes in the manufacturing sector in the high, medium-high, medium-low, and low technology groups. These in turn can be roughly categorized into final or intermediate goods however this would be a very rough proxy.

Patstat contains data on different types of intellectual property. The EPO has simplified this into three categories: PI (patents for invention), UM (utility models), and DP (design patents). In our analysis we restrict to only the first category of patents. Utility models were designed to be a weaker form of intellectual property rights. The innovative requirement is less stringent and it is usually smaller firms that hold utility model patents. Since there are already issues with measuring patent quality, we decide to exclude these patents. Design patents are evidently less relevant innovations however they may be a proxy of marketing techniques or intensity and might have an effect on the firm’s market size and hence competitiveness.

4 Empirical Analysis

Our baseline firm specification is a poisson regression on innovation output with measures of knowledge spillovers, firm competitiveness, and variables defining industry characteristics. We construct two knowledge spillover variables. One that is based on historical collaborators and one based on firm location. We also construct a measure of firm competitiveness defined as the knowledge stock gap between the given firm and the frontier firm in the industry. The industry variables also include a measure of competition (Herfindahl’s index) and various moments of the industry – firm size distribution such as skewness.
5 Conclusion

Firms are the main driver of growth and the link between many policies and consumer welfare. Although there is a broad literature on firms, they have such complex interactions that economists have been forced to focus on specific points in isolation. Here I return to the big picture and review the different strands of literature concerning the firm and its innovation output and I hopefully present new connections and directions for future research.
References


