Essays on Economic Sociology of Innovation and Entrepreneurship

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Abstract

This dissertation considers how innovation and entrepreneurship are developed, encouraged, and evaluated with the theoretical lens of economic sociology. The first chapter investigates who becomes an entrepreneur among the pool of general consumers. The process by which individuals become entrepreneurs is often described as a decisive moment of transition, yet it necessarily involves a series of smaller steps. By breaking down the transition stages of knitting hobbyists’ transition to producers who sell their original design patterns, the study examines the distinctive characteristics that affect users’ decision to (a) create new products and (b) commercialize them.

The second chapter examines the role of social capital in revealing and encouraging entrepreneurship. To the question of how social capital benefits innovation and entrepreneurship, existing literature has provided one dominant answer: access to information and resources. In this study, I suggest an alternative mechanism how social capital benefits an individual’s entrepreneurial transition: social networks provide potential entrepreneurs self-confidence on the promise of their new ideas and encourages their entry into the market. Using a matched sample of potential innovators, I show that an individual’s participation in a local group encourages her transition to an entrepreneur, especially for those who already have the necessary skills for the transition. The empirical analysis resonates with qualitative evidence that hobbyists make the transition to entrepreneurs when encouraged by their friends.

The third chapter (co-authored with Pierre Azoulay and Ezra Zuckerman) considers commitment-based typecasting among knit designers. We show that “commitment-based typecasting” has two characteristic features: asymmetry in audience valuation and retrospective reevaluation. When a novice performer experiences an “identity shock” that suggests that she is more committed to the audience for one category than another, “betrayed” audience tends to regard her as having always been less committed to the rival audience/category. We test this theory in the domain of knitting, where there is a divide between avant-garde knitters and traditional knitters, and we show that when a novice knit designer is first published in the publication associated with one category, this elicits a retrospective devaluation of her prior work by the audience of the opposing category.

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Chapter 1

Sharing or Selling:

Multiple Stages of Entrepreneurial Transitions in the Hobbyist Community

1. INTRODUCTION

Many great innovators and entrepreneurs were once “frustrated users” who were not satisfied with the product or service they were using. Dropbox was founded by an MIT student who frequently forgot his USB flash drive (Pontin, 2012); Houzz was founded by a couple who could not find suitable resources when renovating their new house (Kurutz, 2012); Nike was founded by a track-and-field coach who wanted to make a better running shoe for his students (Moore, 2006); Spanx was founded by a salesperson who was required to wear dress pants at work and hated that the edges of her underwear showed through (O’Connor, 2012). There are many other examples of innovative products and services developed by frustrated users, but an even larger fraction of users who are dissatisfied with existing offerings do not attempt to realize or commercialize their new ideas. This raises the question of how and why some users transition to entrepreneurs while others do not.

Studies emphasizing human capital suggest that entrepreneurs have distinctive skills and capabilities that lead them to create and commercialize their ideas. For example, “jacks-of-all-trades” with careers that span a variety of skill sets are more likely to become entrepreneurs (Lazear, 2004), and consumers with higher educational levels or engineering backgrounds are more likely to innovate (von Hippel, de Jong, & Flowers, 2012). Building on the Austrian school of entrepreneurship, studies also suggest that entrepreneurial opportunities are discovered by those who have specific skills and experiences (Kirzner, 1997; Shane, 2000). Although these theories provide valuable insights into those who have greater capabilities to become
entrepreneurs, not all individuals with such capabilities commercialize their innovations and become entrepreneurs. In other words, highly capable individuals are not necessarily committed to commercializing their innovations and those who are not commercially motivated would not monetize their innovations.

An excellent example is Mollick’s (2016) study about innovators who choose not to commercialize their products. The study shows that software developers who strongly commit to open source software communities are less likely to commercialize their software, even when they already have developed a product. Furthermore, he shows that it is not because those developers have anti-commercial beliefs that software should be shared for free, but because they value their self-identities within the open-source communities in which they participate. That is, the more they value their roles in the community and consider their images in the community to be central to their lives, the less they tend to be motivated to commercialize their product and pursue profits.

The evidence from these software developers implies that those who are highly embedded in the user community can be reluctant to commercialize their products. However, there are also cases where those who are active in the community are more likely to become entrepreneurs. This is because users who can commercialize their products must have a greater interest in the product field than others, and knowledge from the community should build a greater basis for commercialization. For example, in their seminal research on the process of user entrepreneurship, Shah and Tripsas (2007) show that parents found baby product companies benefited greatly from information and feedback from the community, such as local parenting groups and/or online communities. The authors show that both information about the product field and encouragement from members of the community helped users commercialize the
products they created. Studies on the sports-hobbyist community also stress that users’
knowledge gleaned from the community helps users develop their ideas and become innovators
(Franke & Shah, 2003; Lüthje, 2004). Therefore, it appears there is contrasting evidence about
the role of community in users’ entrepreneurial transitions.

One possible way to explain the contrast is to dissemble the transition process by stages
and consider how the contrasting factors affect each stage. The process by which individuals
become entrepreneurs is often observed as a decisive moment of transition, yet it necessarily
involves a series of smaller transitions from being a consumer through launching a business.
Since each transition involves different types of incentives and challenges, it is necessary to
observe each stage separately to understand why some consumers become entrepreneurs while
others do not. In particular, I focus on how the effect of community impacts two stages of the
transition: (a) the transition from general users to producers who create new products and (b) the
transition from producers to entrepreneurs who commercialize their products.

As a setting, I choose knitting hobbyists’ transitions to producers in a knit design market
and analyze the data from Ravelry.com, the largest community and marketplace for knitting
hobbyists. Based on fine-grained data about the full population of knitters, I explore
heterogeneity in the knitters’ experience throughout their transition stages. Specifically, I show
that knitters who make the first transition and create new products tend to have higher levels of
experience and are more committed to the community by serving as voluntary editors, compared
to general users who remain consumers in the knit design market. However, in the later stage of
transition where producers begin to sell their products, these factors have opposite effects. That
is, knitters who make the second transition and sell their products tend to have lower levels of
experience and are less committed to the community by serving as voluntary editors, compared to producers who did not commercialize their products.

The rest of the paper proceeds as follows. In the next section, I develop my hypotheses based on the contrasting theories of the effect of community on entrepreneurial transitions. Section 3 presents my setting of platform-based entrepreneurship among knitting hobbyists and describes my data. Section 4 presents the results of the empirical analysis; Section 5 concludes and discusses the implications of the study.

II. THEORY AND HYPOTHESES

There are two prevailing theories about when community-based producers decide to commercialize. On the one hand, activities in a community can encourage and accelerate its members' commercialization process by providing valuable knowledge about the product field and potential customers. Studies on user innovation provide various examples of communities with this learning effect (Franke & Shah, 2003; Lüthje, 2004; Lüthje, Herstatt, & von Hippel, 2005; Oliveira & von Hippel, 2011; Shah & Tripsas, 2007). By interacting with other members of the community, users can acquire information about which segment of the market is underserved, and launch their business based on the shared experience of frustrated users.

On the other hand, having knowledge about the product and market is necessary but not sufficient to commercialize new products. For example, when Apple launched App Store, many jailbreak software developers who were already sharing their software through an open source community chose not to commercialize their software even though commercializing it was a trivial procedure (Mollick, 2016). Interestingly, those who chose not to commercialize their products were users with stronger self-identities as members of the community than as
entrepreneurs. This identity effect of community suggests that more activities and higher embeddedness in the community can decrease the probability of commercializing products.

In this paper, I suggest that one way to disentangle the contrasting aspects of the community effect is to differentiate stages of the transition. The positive effect of the community to provide knowledge will not be salient among jailbreaking developers who already are sufficiently knowledgeable to make the transition to entrepreneurship. That is, the learning effect may prevail in the early stage of transition when users create new products, while the cost of commercialization becomes a significant decision factor once the desired level of knowledge is achieved through experience in the community.

The cost of commercialization occurs in two ways. First, by commercializing their products and becoming sellers who serve the market, experienced users can no longer fully commit their time and energy to their own experiences as pure hobbyists. Second, the hobbyist community can perceive the act of commercialization as inauthentic behavior since users are monetizing their hobby and pursuing profits in the community (cf. Hahl & Ha, 2016; Kim & Ha, 2019). Therefore, given the trade-offs, those users who wish to remain committed members of the community as pure hobbyists will show a higher level of activities and commitment even after they accumulate sufficient knowledge to create new products, compared with users who choose to commercialize their products. Thus, I hypothesize as follows:

\[ H1a. \text{ A higher level of experience is associated with a user’s transition to a producer.} \]
\[ H1b. \text{ A lower level of experience is associated with a producer’s decision to commercialize.} \]
\[ H2a. \text{ High commitment to the community is associated with a user’s transition to a producer.} \]
\[ H2b. \text{ Low commitment to the community is associated with a producer’s decision to commercialize.} \]
III. DATA AND METHODS

I examine the determinants of the entrepreneurial transitions of knitters. Generally, knitters make a knitting “project” (e.g., a sweater) by following a specific “pattern” designed by a professional designer. A standard knitting pattern consists of pictures of the finished project, information about necessary materials (e.g., yarn and needles), the gauge and sizing, as well as detailed step-by-step instructions. In the market for knit patterns, designers are producers and knitters are consumers who follow patterns to create their projects. Figure 1 shows how this market works.

—Figure 1 goes about here—

Traditionally, knitters accessed new design patterns from knitting magazines, pamphlets provided by local yarn stores, or pattern books. However, through digitization, it is now easier for knitters who create original designs to share their design patterns through their personal blogs or online communities. Since Ravelry.com was launched in 2007 and grew to be the largest online community and marketplace for knitters, the entry barrier to becoming a designer has been lowered even further.

By 2018, Ravelry—the so-called “Facebook of knitters” (Martin, 2012)—served over 7 million registered knitters throughout the world. According to a survey by The National Needle-Art Association, 86% of active knitters reported that they use Ravelry (TNNA, 2013). Ravelry became an important platform for knitters for several reasons. First, it provides an archival system for knitters who want to keep track of their projects. When recording their projects in digital libraries, the knitters include the specific patterns they used in their projects, the characteristics of the yarns used, and the dates they started and finished their projects. In this
way, knitters can conveniently archive the history of their knitting activities in detail. Second, Ravelry serves as a marketplace for knit designers. Nascent designers can easily open designer accounts to run their design shops, and Ravelry provides extensive resources for operating these shops from payment systems to sales analyses. In 2014, 11,500 individual designers—excluding yarn companies and publishers—sold at least one pattern, and they recorded a cumulative total of 11.2 million USD in annual sales. As of 2018, over 20,000 designers were sharing over 700,000 different design patterns through Ravelry.

I use the dataset scraped from Ravelry in May 2017 and categorize the knitters of each stages as follows. Under the following categorization, I study two transitions: one from knitters (a) to designers (b) and the other from designers (b) to selling designers (c).

(a) Knitters (users): A knitter is defined as someone who is registered in Ravelry to look at and use patterns but does not create her own original patterns. In general, knitters follow a specific pattern of a designer to create a project.

(b) Designers (producers): A designer is someone who has a designer account and releases her original patterns. Although Ravelry has made becoming a designer easier than ever, only a minority of knitters became designers. As shown in Table 1, only 3.3% of knitters were designers with at least one pattern in Ravelry. Among all designers, those who do not charge for their designs and share them for free are defined as sharing designers; those who have at least one pattern for sale are categorized as selling designers.

(c) Selling Designers (entrepreneurs): Once a knitter produces a knit pattern, she can either share it for free or sell it for a price. A designer can also do both by selling some patterns while sharing
others for free. Designers who have at least one pattern for sale are defined as selling designers. As shown in Table 1, only 1.5% of knitters become selling designers.

—Table 1 goes about here—

My data on knitters’ entrepreneurial transitions provides two important empirical advantages. First, by focusing on the field of knitting, I can access the entire risk set of user entrepreneurs in the field. Since knitting designers necessarily have experience in knitting before they can become designers, every designer begins her career as a knitter. Therefore, the pool of knitting users serves as an appropriate risk set of user entrepreneurs. Second, the data provides a rare opportunity to observe the usage behavior of future entrepreneurs at a fine-grained level. In general, a user’s transition to becoming an entrepreneur is observable only after they make the transition, so their pre-transition activities are difficult to observe. Since my setting provides pre-transition activities in detail, I can test how those who make the transition are different from those who do not.

The sample includes Ravelry users with at least one project adequately linked to any pattern by the end of 2014. I narrowed the sample to users with identifiable profile pages and location information. Non-US knitters were excluded to control unobserved cultural differences in knitting activities. Furthermore, I excluded knitters who were not appropriate constituents of the risk set. Because my focus is to predict the risk of a knitter’s transition to an entrepreneur, I dropped established designers who were designing before joining Ravelry.¹

¹ Established designers were detected in two ways. First, I excluded knitters whose patterns were listed by other Ravelry users before the designer joined Ravelry. Second, I excluded knitters who retrospectively filed their publication records with the oldest pattern published before 2005. I chose 2005 over 2007 because designers who self-reported that their first pattern was designed between 2005 and 2007 tended to be nascent designers whose careers were motivated more by the availability of online platforms than established designers who had been designing for traditional media.
3.1. Variables

3.1.1. Dependent Variable: Entrepreneurial Transitions

The first transition I examine is the transition of a knitter (user) to become a designer (producer). For a knitter to become a designer, she opens a designer account—which is different from her user account—prepares the page of her store and uploads her original patterns. I consider the moment she releases her first pattern to be her transition to become a designer.

Table 1 shows descriptive statistics for the variables including transitioning to become designers.

The second transition I examine is the transition of a designer (producer) to become a designer who charges for her designs (entrepreneur). I consider a designer who has at least one pattern for sale during the observation period to be an entrepreneur, and the first release of for-sale patterns charging a price to be her transition to become an entrepreneur.

3.1.2. Main Independent Variables

*Level of experience in the community.* Knitters in Ravelry maintain records of the knitting projects they are working on as well as the projects they have completed. The more projects a person lists means the more actively the person has been knitting. Therefore, I use the number of projects as a proxy for the general level of knitting experience. By 2014, the average number of projects per knitter was 10.68. The distribution of the number of projects is highly skewed (median at 2, maximum at 1,583). Therefore, the variable is included in the model as categorical variables with 9 sub categories (0, 1, 2, 3-4, 5-9, 10-19, 20-39, 40-99, 100+). The results remain consistent when the variable is included as a logged value of the number of projects.

*Commitment to the community.* Knitters in Ravelry may volunteer to become editors who update and edit Ravelry patterns and yarn databases. For example, if the publication source of
the pattern (e.g., the names of magazines) is entered in multiple formats, editors can merge the
information and put it in a consistent format. Editors also correctly label patterns that are
classified under a wrong category or technique. There is no financial incentive for knitters to join
the editors’ group, but editors can display the symbol of a medal with the text “voluntary editor”
on their profile pages (see Figure 2 for an example). About 3.5% of knitters in my sample joined
the editors’ group by 2014, and they tended to have higher levels of experience in knitting. The
variable takes a value of 1 once the knitter joins the editors’ group and remains as 1 for the
duration of the observation period.

—Figure 2 goes about here—

3.1.3. Other Variables

Technical experience. Every pattern indicates specific knitting techniques that are
required to finish the pattern’s project. Ravelry has categorized 50 knitting techniques that are
linked to the patterns, including 7 color-work techniques (e.g., Intarcia, mosaic, stripes), 27
construction techniques (e.g., one-piece, worked flat, worked in the round), and 16 fabric
techniques (e.g., cables, lace, ribbed). To measure the level of technical experience, I use the
number of different techniques the knitter has tried throughout her projects until time t when the
variable is measured. On average, a knitter had tried 9.75 techniques by 2014 with a median of 6
and a maximum of 49.

Market experience. Based on the 26 pattern categories that Ravelry suggests (e.g.,
sweater, coat, dress, bag, hat, blanket, softies), I examine whether the likelihood of becoming a
designer increases when the knitter experiences more diverse market segments of different
product categories. The variable counts the number of different categories from which the knitter
has made a project until time t when the variable is measured. By 2014, a knitter on average experienced 3.21 product categories, with a median of 2 and a maximum of 25.

Repeated applications. Although over 700,000 patterns are available in Ravelry, knitters often work on the same pattern they previously completed. For example, a knitter can create 10 projects that apply the same hat pattern but with different colors of yarn. In this case, I consider the 9 follow-on projects of the knitter after her first project of the specific hat pattern as “repeated projects.” On average, 12% of projects are repeated projects. The variable is measured by the number of repeated projects divided by the number of all projects.

Disobedient applications. When a designer writes a pattern, she can suggest a specific kind of yarn that is best for making that pattern and knitters can use their discretion about whether to follow her suggestion. A knitter is more likely to achieve the expected results when she follows the suggestion, as different yarns are made of different materials and have different degrees of thickness or softness. I use the proportion of projects using the same yarn suggested by the designer as the knitter’s tendency to obey the suggestion. By “the same yarn,” I refer to the same product line of the same brand, but not necessarily the same color. For example, Belle 8-ply Superwash yarn of the brand name Red Riding Hood Yarns is one kind of yarn, regardless of whether its colorway is Cherry Blossom or Lavender. About 26.5% of projects are constructed with the same yarn as suggested by the designer.

Completeness of yarn information. Since project information is self-reported and yarn specifications are not mandatory, all knitters do not indicate the kinds of yarns they employed in their knitting projects. The proportion of projects using suggested yarns significantly differs by the number of projects with yarn information, thus I included the ratio of projects with yarn information as a control variable.
In addition, the time effect with the number of years the knitter has spent in Ravelry (8 indicator variables), and 29 indicator variables for each quarter are included to control both the seasonal effect and the lifecycle effect of the website or of knitting in general.

3.2. Model

To analyze the determinants of user’s transitions to entrepreneurship, I employ discrete-time hazard rate models (Allison, 1982; Azoulay, Ding, & Stuart, 2007). The hazard rate with time and other covariates is as follows:

\[
\ln \left( \frac{p_{it}}{1 - p_{it}} \right) = \alpha_t + \beta' X_{it}
\]

where the hazard rate is \( p_{it} = \Pr[T_i = t | T_i \geq t, X_{it}] \). \( T_i \) is the time at which knitter \( i \) becomes a designer, \( X_{it} \) is a vector of covariates, and \( \alpha_t \) is a set of time variables. In practice, I estimate a logit of the transition where the sample consists of each quarter for every knitter. The model incorporates the time effect with the number of years the knitter has spent in Ravelry (8 indicator variables). Covariates are measured at each quarter, and 29 indicator variables of each quarter are also included.

Once a knitter becomes a designer, her post-transition observations are omitted as they are no longer at risk of another transition. Knitters who did not make the transition were observed for the full period from when they joined Ravelry to the end of 2014. My final sample for this human capital analysis consists of 6,798,353 knitter-quarter observations for 403,168 individual knitters.

The purpose of this analysis is to find leading indicators of the transition to entrepreneurship among the correct set of users by each stage. The analysis shows which knitters are more or less likely to transition, but it does not make any causal claim as knitters’ experience
and commitment can be accumulated endogenously with the knitters’ decisions to become entrepreneurs. Note also that the analysis does not include individual knitter fixed effects, thus focusing on between-individual variations to identify the determinants of entrepreneurial transitions. An additional analysis with individual knitter fixed effect is presented in section 4.3. to provide further insights.

IV. RESULTS

4.1. Descriptive Statistics

Table 1 presents the summary descriptive statistics for main variables. Table 2 presents the mean characteristics of each type of knitter—pure users who never became either sharing designers or selling designers until the end of the observation period, sharing designers who created and released at least one original pattern, and selling designers who created and sold at least one original pattern—by their tenure in Ravelry. The first section compares three types of knitters at the end of their first year in Ravelry. It shows that future designers, either sharing or selling, tend to have much higher levels of expertise and commitment even in the very first year of their experiences in Ravelry. They have higher numbers of project applications and higher rates of joining the voluntary editors’ group. Also, it shows that sharing designers tend to have slightly higher levels of experience and commitment to the community than selling designers in this cross-sectional comparison.

The second section compares three types of knitters at the end of their third year in Ravelry. It shows that the characteristics shown in the first section grow stronger as their experience in Ravelry accumulates. Both sharing designers and selling designers show higher
levels of experience and commitment to the community compared to pure users, while the levels are slightly higher for sharing designers compared to selling designers.

—Table 2 goes about here—

4.2. Discrete-time Hazard Rate Models

Table 3 shows the results of a discrete-time hazard model without individual fixed effects. Model 1 shows the effect of knitting experience variables on the first transition, a knitter’s transition to becoming a designer. Models 2 analyzes the second transition, a designer’s transition to becoming an entrepreneur by selling their patterns.

—Table 3 goes about here—

First, the number of projects positively associates with the probability of transition from a knitter to a designer. That is, a knitter is more likely to create new products as she accumulates general experience in knitting by making more projects (H1a). However, those who choose to monetize their designs tend to spend less time creating projects, compared to sharing designers (H1b). Second, the probability of becoming a designer increases as the knitter joins the voluntary editors’ group (H2a). However, those who choose to monetize their designs tend to contribute less to the community by serving as voluntary editors, compared to sharing designers (H2b).

4.3. Fixed-effect Linear Probability Models

For an additional test controlling unobserved individual characteristics, I also tested the effect of knitting experience variables with individual fixed effects. However, logit estimation is not applicable because conditional maximum likelihood estimation requires variation in the dependent variable, while my sample includes the full set of knitters who have not made the entrepreneurial transition until the end of the observations. As an alternative approach, I chose a
linear probability model to examine whether the variables tested in the discrete-time hazard model show consistent effect on the transition when controlling unobserved characteristics of individuals. The results are presented in Table 4.

—Table 4 goes about here—

The results show that the clear contrast between the first transition and the second transition disappears with the individual fixed effect, suggesting that the effects shown in Table 3 are mostly driven by cross-individual differences (including unobserved characteristics) than the changing behavior of knitters by stages. On the one hand, the results with individual fixed-effect consistently support the learning effect within individuals. That is, their higher levels of experience and commitment to the community leads them to become entrepreneurs, increasing the probability of both creating new products and commercializing the products. On the other hand, the results imply that the possible community effect in discouraging entrepreneurial transitions is mostly driven by the varying cost of commercialization between individuals, rather than the increasing cost of commercialization as they become more committed to the community.

V. CONCLUSION AND DISCUSSION

These results offer valuable insights about which users become entrepreneurs and how they differ from users who remain users. Based on detailed observational data on users, I examine how users’ accumulated experience in the community affects (a) their transitions to producers who create new products and (b) their follow-up transitions to entrepreneurs who sell their products. In particular, I show that more experienced and committed knitters tend to make the first transition and create new products, while knitters who make the second transition and
sell their products tend to be less experienced and committed compared to sharing producers who do not commercialize their products.

The results show the characteristics associated with users’ transitions to entrepreneurship at each stage, but these associations are not necessarily causal. On the one hand, it is possible that unobservable entrepreneurial characteristics of some users are reflected in both their knitting activities and entrepreneurial transitions. For example, those who have a certain personality that drives them not to follow the product instructions will show higher ratios of disobedient project applications. The clear contrast between the first stage and the second stage of the transition process in the analysis without individual fixed effect is mostly driven by this cross-individual difference. On the other hand, future designers might accumulate their experiences in ways that reduce the cost of transition. For example, by not following the suggestions of designers and choosing different yarns, the knitter can learn how to make modifications in the gauge or the sizing of the project. In this case, the results imply that improvement in skills increases the probability of entrepreneurial transition. The results with individual fixed-effect reflect this learning effect within individuals, and support that their higher level of experience in the community leads them to become entrepreneurs, increasing the probability of both creating new products and commercializing the products.

This study contributes to the literature of user innovation and entrepreneurship in three ways. First, the study provides empirical evidence that disentangles the puzzle around the community effect on entrepreneurship. Based on two contrasting theories of learning effect (e.g., Shah & Tripsas, 2007) and identity effect (e.g., Mollick, 2016), it shows that the accumulation of experience and commitment can facilitate users’ transition to producers who create new
products, while the strong self-identity of experienced and committed users can discourage the second transition to commercialize their products.

Second, the study contributes to the literature of user entrepreneurship by providing empirical evidence about the differences between those who make the transition and those who do not at each transition stage. The classical approach to study user innovation has been either to identify “user” innovators among a set of innovators and compare their characteristics with other types of innovators (e.g., profit-seeking firms), as most user-based entrepreneurs can be observed only after they have become nascent entrepreneurs. Even if we were to identify the broad set of users who are at risk of becoming entrepreneurs, it would still be difficult to observe their consumption activities and measure their actions. Accordingly, recent studies depend on self-reported answers in surveys of general users (von Hippel et al., 2012; von Hippel, Ogawa, & De Jong, 2011) or the small set of users in a specific field (Franke & Shah, 2003; Lüthje, 2004; Oliveira, Zejnilovic, Canhão, & von Hippel, 2015). In this study, by focusing on the field of knitting hobbyists and analyzing comprehensive data about the community in which the majority of them participate, the study finds a rare opportunity to study the entire population of potential entrepreneurs.

Third, and more broadly, the study shed lights on the novel phenomenon of “platform-based hobbyist entrepreneurship.” Previous studies on the entrepreneurial process have focused on the transition from employment to self-employment (Carroll & Mosakowski, 1987; Giannetti & Simonov, 2009; Lazear, 2005). However, the entrepreneurial process cannot be reduced to this classification as a growing number of entrepreneurial entries do not involve a sharp transition in employment status. For example, if you make furniture or jewelry, you can easily open a shop and sell on Etsy, an online marketplace for crafts comprising two million active shop owners by
2016. If you have a specific product idea but lack the necessary resources to turn your idea into a product, Maker’s Row can connect you with a manufacturing partner from among 1,400 US factories. If you want to launch a service business, such as catering or plumbing, Thumbtack connects 250,000 small business professionals to local users. Providing someone has an idea and intent to sell, the entry barrier has been greatly lowered and the opportunity cost can be minimized.

With this context in mind, “platform-based hobbyist entrepreneurship” can be both a valuable context for observing and understanding key early stages in the entrepreneurship process as well as an important phenomenon *per se* of the new economy. Similar cases of entrepreneurial transition on various online platforms include Etsy (craft producers), Bevv (craft breweries), Udemy (teaching content producers), SumZero (analysts), and YouTube (video channel owners). As a wide variety of online platforms open opportunities for hobbyists to become entrepreneurs, this study can provide more general insight about who becomes a producer and who decides to commercialize.
REFERENCES


Table 1. Descriptive statistics, full sample

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>S.D.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Time-varying (6,798,353 knitter-quarter observations)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transition to designer</td>
<td>0.0019</td>
<td>0.0439</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Transition to entrepreneur</td>
<td>0.0007</td>
<td>0.0255</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Number of projects</td>
<td>7.307</td>
<td>17.820</td>
<td>0</td>
<td>1,583</td>
</tr>
<tr>
<td>Number of knitting techniques applied</td>
<td>7.798</td>
<td>8.390</td>
<td>0</td>
<td>49</td>
</tr>
<tr>
<td>Number of product categories explored</td>
<td>2.522</td>
<td>3.064</td>
<td>0</td>
<td>26</td>
</tr>
<tr>
<td>Proportion of repeated projects</td>
<td>0.039</td>
<td>0.103</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Proportion of disobedient applications</td>
<td>0.213</td>
<td>0.379</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Completeness of yarn information</td>
<td>0.100</td>
<td>0.186</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Ever joined the Ravelry editors’ group</td>
<td>0.006</td>
<td>0.075</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Calendar quarter</td>
<td>2012Q2</td>
<td>7.118</td>
<td>2007Q3</td>
<td>2014Q4</td>
</tr>
<tr>
<td>Years using Ravelry</td>
<td>2.563</td>
<td>1.804</td>
<td>0</td>
<td>7</td>
</tr>
</tbody>
</table>

**One observation per knitter, 403,168 knitters (last observation of each knitter)**

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>S.D.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Designers</td>
<td>0.033</td>
<td>0.178</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Entrepreneurs</td>
<td>0.015</td>
<td>0.123</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Quarter joined Ravelry</td>
<td>2010Q4</td>
<td>7.866</td>
<td>2007Q2</td>
<td>2014Q4</td>
</tr>
</tbody>
</table>
Table 2. Knitters’ mean characteristics by transition stages

<table>
<thead>
<tr>
<th></th>
<th>Pure users</th>
<th>(future) Sharing designers</th>
<th>(future) Selling designers</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ravelry Tenure = 1 year (4 quarters)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level of experience (Number of projects)</td>
<td>3.202 (6.635)</td>
<td>11.234 (14.590)</td>
<td>10.473 (15.695)</td>
</tr>
<tr>
<td>Commitment (Editor status)</td>
<td>0.003 (0.053)</td>
<td>0.030 (0.170)</td>
<td>0.030 (0.171)</td>
</tr>
<tr>
<td>Technical experience</td>
<td>5.268 (6.055)</td>
<td>11.290 (9.248)</td>
<td>10.236 (9.674)</td>
</tr>
<tr>
<td>Market experience</td>
<td>1.679 (2.099)</td>
<td>4.145 (3.733)</td>
<td>3.618 (3.718)</td>
</tr>
<tr>
<td>Proportion of disobedient applications</td>
<td>0.145 (0.333)</td>
<td>0.424 (0.438)</td>
<td>0.361 (0.432)</td>
</tr>
<tr>
<td>Proportion of repeated projects</td>
<td>0.029 (0.096)</td>
<td>0.068 (0.119)</td>
<td>0.064 (0.122)</td>
</tr>
<tr>
<td>Number of observations</td>
<td>361,867</td>
<td>6,862</td>
<td>6,141</td>
</tr>
</tbody>
</table>

| **Ravelry Tenure = 3 year (12 quarters)** |            |                            |                           |
| Level of experience (Number of projects) | 7.451 (15.429) | 30.497 (34.959) | 31.035 (37.491) |
| Commitment (Editor status)           | 0.005 (0.070) | 0.052 (0.222) | 0.064 (0.245) |
| Technical experience                 | 8.558 (8.068) | 18.589 (10.429) | 17.813 (11.410) |
| Market experience                    | 2.764 (2.991) | 7.162 (4.625) | 6.639 (4.818) |
| Proportion of disobedient applications| 0.227 (0.386) | 0.571 (0.398) | 0.512 (0.417) |
| Proportion of repeated projects      | 0.044 (0.108) | 0.102 (0.124) | 0.107 (0.140) |
| Number of observations               | 279,634     | 6,092                      | 5,478                     |
Table 3. Discrete-time hazard rate models

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>[1]</th>
<th>[2]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Users’</td>
<td>Designers’</td>
</tr>
<tr>
<td></td>
<td>Transitions to</td>
<td>Transitions to</td>
</tr>
<tr>
<td></td>
<td>Designers</td>
<td>Entrepreneurs</td>
</tr>
<tr>
<td>Number of knitting projects</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(baseline category is 0 project)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 project</td>
<td>0.057</td>
<td>-0.530***</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.090)</td>
</tr>
<tr>
<td>2 - 3 projects</td>
<td>0.725***</td>
<td>-0.742***</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.091)</td>
</tr>
<tr>
<td>4 - 10 projects</td>
<td>1.511***</td>
<td>-1.021***</td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>(0.096)</td>
</tr>
<tr>
<td>11 - 30 projects</td>
<td>2.158***</td>
<td>-1.052***</td>
</tr>
<tr>
<td></td>
<td>(0.070)</td>
<td>(0.118)</td>
</tr>
<tr>
<td>31 - 100 projects</td>
<td>2.630***</td>
<td>-0.935***</td>
</tr>
<tr>
<td></td>
<td>(0.092)</td>
<td>(0.147)</td>
</tr>
<tr>
<td>100+ projects</td>
<td>2.998***</td>
<td>-0.612**</td>
</tr>
<tr>
<td></td>
<td>(0.124)</td>
<td>(0.190)</td>
</tr>
<tr>
<td>Joining the voluntary editors’ group</td>
<td>0.988***</td>
<td>-0.068</td>
</tr>
<tr>
<td></td>
<td>(0.051)</td>
<td>(0.073)</td>
</tr>
<tr>
<td>Number of different knitting techniques applied</td>
<td>-0.026***</td>
<td>0.024***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Number of different product categories explored</td>
<td>0.089***</td>
<td>-0.083***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Proportion of disobedient applications</td>
<td>0.131***</td>
<td>-0.279***</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.059)</td>
</tr>
<tr>
<td>Proportion of repeated applications</td>
<td>0.363***</td>
<td>0.234</td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.157)</td>
</tr>
<tr>
<td>Constant</td>
<td>-6.262***</td>
<td>-0.968**</td>
</tr>
<tr>
<td></td>
<td>(0.125)</td>
<td>(0.367)</td>
</tr>
<tr>
<td>Pseudo R squared</td>
<td>0.089</td>
<td>0.073</td>
</tr>
<tr>
<td>N individuals</td>
<td>403,168</td>
<td>13,130</td>
</tr>
<tr>
<td>N observations</td>
<td>6,798,353</td>
<td>110,822</td>
</tr>
</tbody>
</table>

Note: Robust standard errors in parentheses, clustered around each knitter. 29 indicator variables for each quarter, 8 indicator variables for the knitter’s tenure (by year) at Ravelry, and the degree of completeness in yarn information are included in the model. Established designers who published a pattern before Ravelry became available are excluded. *p<0.05, **p<0.01, ***p<0.001
Table 4. Linear probability model with individual fixed effects

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of knitting projects</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(baseline category is 0 project)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 project</td>
<td>0.002***</td>
<td>0.029***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>2 - 3 projects</td>
<td>0.003***</td>
<td>0.049***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>4 - 10 projects</td>
<td>0.005***</td>
<td>0.058***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>11 - 30 projects</td>
<td>0.008***</td>
<td>0.070***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>31 - 100 projects</td>
<td>0.012***</td>
<td>0.077***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>100+ projects</td>
<td>0.015***</td>
<td>0.085***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Joining the voluntary editors’ group</td>
<td>0.040****</td>
<td>0.024*</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Number of different knitting techniques applied</td>
<td>-0.000***</td>
<td>0.002***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Number of different product categories explored</td>
<td>0.002***</td>
<td>0.002***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Proportion of disobedient applications</td>
<td>-0.000</td>
<td>-0.000</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Proportion of repeated applications</td>
<td>0.007***</td>
<td>0.036*</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.020***</td>
<td>-0.144***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.029)</td>
</tr>
</tbody>
</table>

Note: Robust standard errors in parentheses, clustered around each knitter. 29 indicator variables for each quarter, 8 indicator variables for the knitter’s tenure (by year) at Ravelry, and the degree of completeness in yarn information are included in the model. Established designers who published a pattern before Ravelry became available are excluded. *p<0.05, **p<0.01, ***p<0.001
Figure 1. Market for knit patterns

Note: In an online marketplace for knit patterns, designers (producers) sell patterns to knitters, and knitters (users) buy the patterns to create their projects. Designers can either share their patterns for free or sell them. Both sharing designers and selling designers earn recognition by fellow knitters who use and cite their patterns.
Figure 2. Presentation of editor status

This Is My ID

.volunteer editor

Raveler since
Website or blog
Location
Pets? Kids?
Favorite colors

About me
Chapter 2

Knitting Community:

The Role of Social Capital in Revealing and Encouraging Entrepreneurship

1. INTRODUCTION

Great artists, inventors, and entrepreneurs often emerge from local communities of like-minded people (Fleming & Marx, 2006; Saxenian, 1996). Beethoven benefited greatly from Vienna’s music community (DeNora, 1991); star scientists are concentrated in locations with strong academic communities (Zucker & Darby, 1996); and renowned entrepreneurs launched their business within the entrepreneurial community in Silicon Valley (Saxenian, 1996). The advantage of creative individuals being positioned in innovative communities has been explained in large part by the benefit of social capital—“friends, colleagues, and more general contacts—through whom you receive opportunities to use your financial and human capital” (Burt, 1992, p9).²

Why is social capital beneficial to entrepreneurship and how does it promote innovation and entrepreneurship? The dominant mechanism shown in previous studies is access to knowledge and information. That is, social capital opens opportunities for actors to aggregate and recombine information from various other actors within and across communities, and this leads to the generation of novel business ideas (Ahuja, 2000; Burt, 2004). Although the majority of empirical studies about the effect of social structures on innovation and entrepreneurship are based on this mechanism of knowledge transfer, a caveat is that the mechanism focuses on the

² There are multiple definitions of social capital. It is often very narrowly defined as the resources individuals or groups can access through relationships, while the classical definitions from Coleman (1988) tend to be broader (see Portes (1998) for further discussion on the definition of social capital).
idea generation process and cannot be applied to the execution of new ideas. Put differently, being well-positioned in the flow of information may stimulate idea-generation, but it might not shift inventors into entrepreneurs. In fact, the evolution into becoming an entrepreneur requires different mechanisms than knowledge recombination; it involves mobilization of required resources as well as transitions in the actor’s career and role.

Still, recent studies on entrepreneurial transitions have also shown the positive effect of peers and social capital on entrepreneurial transitions (Aldrich & Zimmer, 1986; Eesley & Wang, 2017; Kacperczyk, 2013; Nanda & Sørensen, 2010; Stuart & Ding, 2006; Tartari, Perkmann, & Salter, 2014) and there are reasons why locating within an entrepreneurial community would facilitate new ventures even after the idea generation process. The most probably reason for this effect would be access to resources that facilitate the launch of new businesses (Burton, Sørensen, & Beckman, 2002). Being embedded in a community of successful entrepreneurs allows nascent entrepreneurs better access to venture capital financing, business partnership opportunities, and knowledge about improving their products and businesses. Such tangible benefits are the primary reasons why the choice of location for a new business matters and siting a new venture in Silicon Valley can enhance entrepreneurial performance (Guzman, 2019).

However, another stream of studies suggests a broader role for social capital that cannot be reduced to the provision of resources or knowledge. For example, Sorenson and Audia (2000) show that the geographic concentration of the shoe industry is maintained by continued entrepreneurial entries to the region, but this is not because the region provides better resources to entrepreneurs since new firms in the region are more likely to fail. Giannetti and Simonov (2009) also show that the positive peer effect of entrepreneurship is driven by nonpecuniary
benefits, as the effect is higher among communities where the relative economic returns of entrepreneurship are low. Studies on academic entrepreneurship also suggest that the role of social capital in promoting (or discouraging) entrepreneurship is not confined to opportunity-based factors but extends to attitudinal factors (e.g., Stuart & Ding, 2006). Based on these observations, the study suggests and shows two mechanisms that constitute this broader role of social capital in facilitating entrepreneurship that cannot be reduced to the resource provision and often described as entrepreneurial culture (Sorenson, 2017) or entrepreneurial climate (Reynolds & White, 1997).

First, social capital can augment motivation by encouraging actors to take the next step. Zuckerman and Sgourev (2006) document that one of the roles of social capital in industry peer networks that are common in the small business sector is not only to learn from each other but to augment motivation and raise aspiration levels. Recent studies on the geographic spillover of entrepreneurship also describe a similar social process by which local peers shape aspiration levels and increase the social attractiveness of entrepreneurship (Sorenson 2017; Sorenson & Audia 2000; Giannetti & Simonov 2009). Examples of the particular role of social capital in encouraging individuals to seize economic opportunities can also be found in the role of neighborhoods promoting stock market participation (Hong et al. 2004) and the performance effect of meetings among owner-managers of young firms (Cai & Szeidl, 2017).

Second, social capital can provide opportunities for learning about oneself by revealing talented individuals. This differs from learning about business opportunities or accruing knowledge from other actors in the community that enhances business execution; peer feedback gives information about the abilities of the actor herself through interaction with the demand side (i.e., potential customers) (Jovanovic, 1979). Recent studies on entrepreneurship also suggest
that peers help actors better understand the merits of proposed business ideas (Lerner & Malmendier, 2013) and venture competitions are most useful for getting feedback (Howell, 2018). This role of social capital to provide peer feedback can be especially salient in the earlier stages of the entrepreneurial process when actors who are considering whether to start a business take the lowest-cost steps, such as talking to their family and friends and getting feedback (Bennett & Chatterji, 2017).

In this study, I focus on these two mechanisms of encouraging and revealing and present both qualitative and quantitative evidence of their effects. Although previous literature has been suggestive to the possibility of mechanisms other than resource provision, evidence is limited mostly due to the empirical challenges; both the transition to entrepreneurship and access to social capital are not only difficult to track but also rely heavily on resources available to the actors. One way to disentangle the mechanisms is by investigating for whom the social capital makes the largest difference. When the main role of social capital is to provide resources, it helps individuals compensate for their lack of human capital. Evidence from several studies resonates with this explanation, as the peer effect is shown to be higher for those with lower levels of entrepreneurial resources (Eesley & Wang, 2017; Nanda & Sorensen, 2010; Stuart & Ding, 2006; Tartari et al., 2014). However, when the role of social capital is not to provide education but to reveal talented individuals and encourage them, the effect should be higher for those who already possess entrepreneurial human capital. Using a fine-grained measure of entrepreneurial human capital and a unique shock in the actors’ access to social capital, I show evidence that social capital has a higher effect on those who possess entrepreneurial human capital in my research setting. Also, the qualitative evidence suggests that the primary mechanism of social capital for facilitating entrepreneurship is to reveal talented individuals and encourage them.
Specifically, I study an online marketplace for knit patterns, Ravelry.com, where a minority of the knitting hobbyists transition to become designers who create and sell their original design patterns. Using data on 403,199 individual knitters’ activities between 2007 and 2014, I first find that some knitters—“creative knitters”—have significant skills and demonstrate their abilities to create original designs but do not necessarily produce their designs to share with or sell to other knitters. Qualitative evidence shows that the motives and skills of creative knitters are almost identical to those of designers, and the only difference between them is the existence of social networks that trigger them to become designers. Based on this observation, I quantitatively test the effect of knitters’ encounters with their peers on their transitions to becoming designers. To vary the degree of exposure to peer feedback and encouragement, I use a shock in a knitter’s potential encounters with fellow knitters. Specifically, I measure the effect of a knitter joining a local networking group whose members’ primary purpose is motivating and supporting each other. With a closely matched sample of potential designers, the difference-in-difference analysis shows that joining such a local group increases the probability of entrepreneurial transition by 25 percent.

In addition, I find that this effect is particularly strong among creative knitters who already have developed new ideas and have a higher potential to create new products. Qualitative evidence suggests that this is because creative knitters are the first to be encouraged and to receive positive feedback. About half of the designers I interviewed mentioned that they had been creative knitters for years, but it was not until they were encouraged by their fellow knitters and friends that they actually codified their designs so they could be sold to others. According to those designers, social capital helped them “get over their shyness and develop self-confidence in their designs.” This is especially important for early entrepreneurial transitions of users who
"think the biggest personal challenge is believing in yourself—that what you are creating is something that is desired and valued by others." I also constructed a measure of entrepreneurial human capital based on analyzing the transition probability with the full population of knitters and analyzed to whom the social capital effect is the most salient. The results suggest that the social capital effect is strongest for those who had already developed high levels of entrepreneurial human capital, as users who have better skills are more likely to be encouraged by their close peers.

The rest of the paper proceeds as follows. In the next section, I describe my research setting as well as the empirical advantage and generalizability of the setting. Section 3 presents my qualitative evidence on creative knitters and designers that shows the role of social capital in revealing and encouraging entrepreneurial transitions. Section 4 presents my quantitative analysis of the effect of social capital on entrepreneurial transition. Section 5 concludes and discusses the implications of the study.

II. SETTING

I examine the entrepreneurial transitions of knitters in the market for knit design patterns. Generally, knitters make a knitting “project” (e.g., a sweater) by following a specific “pattern” designed by a professional designer. Therefore, in the market for knit patterns, designers are producers and knitters are consumers who follow patterns to create their projects.

I use the dataset scraped from Ravelry in May 2017. Ravelry.com—the so-called “Facebook of knitters”—was launched in 2007 and grew to be the largest marketplace for knitters. By 2014, 11,500 individual designers—excluding yarn companies and publishers—sold
at least one pattern on Ravelry, and they recorded a cumulative total of 11.2 million USD in annual sales.

In the market for knit patterns, I define entrepreneurial transitions of users as: knitters who transition to become designers and charge for their original patterns. According to the definitions below, it is the entrepreneurial transition from knitters—either passive (a) or creative (b)—to entrepreneurs (d). Table 1 provides a detailed categorization of knitters in Ravelry and their descriptive statistics.

(a) Passive knitters: People registered in Ravelry who look at and use patterns but do not create their own original patterns. Most knitters in Ravelry are passive knitters.

(b) Creative knitters: A small subset of knitters who create original projects but are neither passive knitters nor designers. They differ from passive knitters because they do not blindly follow others' patterns. They differ from designers because they do not have designer accounts nor do they codify their design patterns to share with or sell to other knitters. In the market for knit patterns, they remain as consumers of patterns. Empirically, I operationalize creative knitters as those who indicate that they incorporated two or more patterns to create their projects rather than applying one pattern exactly. For example, if a knitter created an original hat project that included elements of sweater pattern X and another hat pattern Y, her project is not associated with an existing pattern but is categorized as a new project incorporating patterns X and Y. If a knitter created at least one project that incorporates another's designs, she is considered a creative knitter.

(c) Sharing designers: A designer is who has a designer account and who produces designs to share with others. The comparison between sharing designers (c) and entrepreneurs
(d) is discussed in detail in the first chapter of this dissertation and will not be considered explicitly in this chapter.

(d) Entrepreneurs: Once a knitter produces a knit pattern, she can either share it for free or sell it for a price.\(^3\) Also, a designer can do both by selling some patterns while sharing others for free. Designers who have at least one pattern for sale are defined as entrepreneurs. Although Ravelry makes becoming an entrepreneur easier than ever, a small minority of knitters became entrepreneurs. As shown in Table 1, only 1.5% of knitters became entrepreneurs.

—Table 1 goes about here—

While the hobbyist niche of knitting may seem idiosyncratic, there are at least two important reasons to believe it has broad implications. First, the setting resembles many other cases of entrepreneurial transition in various online platforms such as Etsy (craft producers), Udemy (teaching-content producers), SumZero (analysts), Thumbtack (local service providers), YouTube (video channel owners), etc. As a wide variety of online platforms open opportunities for users to become producers, this study can provide more general insight on who becomes a producer and what triggers the transition. Second, hobbyists per se play an important role in entrepreneurship generally. According to a nationally representative survey of US business founders, 27% of founders started their businesses as leisure activities or hobbies (Kim, Longest, & Lippmann, 2015). Furthermore, the boundary between one’s hobby and one’s work is becoming blurry, and an increasing number of nascent entrepreneurs split their time between

\(^3\) Another way to become a paid designer is by submitting patterns to magazine or book publishers. Selling patterns to printed publications was the major route to becoming a professional designer for decades before online marketplaces emerged. The print publication route is not considered in this study for two reasons. First, most designers who sell their patterns to print publications tend to be established designers. Therefore, they are excluded from the sample assembled to study the transition to becoming a designer. Second, many magazines now allow designers to sell their patterns via online marketplaces, and one can publish in print and sell online at the same time.
employment and leisure activities (Lévesque & Schade, 2005). Therefore, understanding hobbyists’ entrepreneurial entries is important to understanding who becomes an entrepreneur and what triggers the transition in general.

III. QUALITATIVE EVIDENCE

To make progress on the question why some users become entrepreneurs while others do not, I first identify a subset of talented users who did not become entrepreneurs—“creative users”—as a comparison group of entrepreneurs who made the transition. I then present qualitative evidence that users’ social capital play an important role in facilitating the entrepreneurial transition.

As shown in Table 1, creative knitters have similar knitting experience with sharing designers or entrepreneurs. Their level of expertise is significantly higher than passive knitters who follow designers’ patterns exactly. To investigate what drives some users to make entrepreneurial transitions while others with necessary skills and experiences remain creative knitters, I conducted an archival study on the designers and creative knitters in Ravelry.

The main sources I used to study designers include the interview sections of Patternfish newsletters (N=50) and three interview-intensive blogs (35 interviews by Kimberly Golynskiy of Around the World in 80 Skeins, 11 interviews by Jean Clement of Desert Rose Fiber Art, and 8 interviews by Marie Segares of Underground Crafter). I chose these sources because (a) to my knowledge they provide the most extensive interviews—employing the same format—on multiple designers and (b) they ask how the interviewee became a designer. In answering that question, 70% of interviewed designers shared a story about what motivated their transition. To supplement the interviews, I also used information found in the Ravelry store accounts and
personal blogs of the interviewed designers. Because four designers interviewed with more than one of the interviewers, the sample for this qualitative study includes 99 designers.

I also collected stories by creative knitters in the Ravelry discussion forums for “modifiers” who do not follow an exact pattern and modify it to their taste. By comparing stories by those who made the transition to designers with those who did not, the following patterns emerged: (a) both creative knitters and designers create new designs, and the reasons for creating new designs are very similar, (b) most designers were creative knitters who became designers when encouraged by people in their social networks, and (c) social feedback is the mechanism by which knitters’ networking affects their transitions.

First, the motive to become a creative knitter seems very similar to that of becoming a designer. Many creative knitters mentioned that they had never really followed a pattern, and the reasons why they created their original projects were to satisfy their creative urges and to feel a sense of independence. Most designers also had been heavy modifiers of patterns. According to the interviews, 55% of designers in the sample specifically mentioned their tendency not to follow the patterns line by line, and only 9% of them mentioned their past experience as passive knitters. Many of them described their experience of designing as they “have been always designing since they [I] learned knitting.” Both designers and creative knitters also mentioned their experience as frustrated users, as “I was having a hard time finding patterns that fit my style (a designer),” or “I never have a fitting sweater if I follow the pattern blindly (a creative knitter).”

Although both designers and creative knitters tend to be heavy modifiers from the outset and satisfy their specific needs and creative urges through generating projects from their original designs, only designers made the transition. One possible trigger can be a reduction in
opportunity cost (Amit, Muller, & Cockburn, 1995; Kacperczyk, 2012; Shah & Tripsas, 2007). For example, Shah and Tripsas (2007) suggest that one reason parent users create the majority of children’s products companies is that the potential founders are on parental leave and face lower opportunity costs. This is also observed in the setting of entrepreneurial transition among knitters. Eight percent of designers explained that they started their ventures when they were in situations during which they focused on knitting (e.g., illness, unemployment, pregnancy, immigration, etc.). However, the opportunity cost of knitters in general has been significantly reduced by the introduction of Ravelry, as the platform provides every administrative and technical support service needed for potential designers. In fact, 4% of designers answered that their transitions to become designers were encouraged by the existence of Ravelry and other technical advances. On the other hand, 3% mentioned financial reasons, 7% transitioned naturally from relevant jobs such as fashion designing, and 13% mentioned a specific piece they needed to make or a specific customer (usually their child) they wanted to fit.

In addition to those answers, the most salient reason that was suggested by 35% of designers in the sample (i.e., 50% of designers who shared any story) was encounters with and encouragement from people they knew. As shown in the quotes below, most designers had been generating new design ideas even before they began to codify and share their designs, and the critical moment of making their entrepreneurial transition came when they were encouraged by people they encountered.

“I had been designing things for myself for a couple of years and my knitting friends kept encouraging me to write up the patterns.”

“Someday, someone from my knitting group, Euskadi Knits, asked for the pattern of some improvised mittens... and I started to write down what I was doing... and I ended up as an amateur designer.”
“Only when people started asking for my chess pattern, did I decide to become a full-time designer. I don’t know why the idea never occurred to me before, but I just knew I had to go for it!”

Oftentimes, the encouragement comes from non-knitters, such as a spouse. One designer recalled, “My husband is the one who got me to design in the first place. He watched me knit from other people’s patterns, and remarked that I never could completely follow one as written. I’d change a neckline here, add pockets there, re-work the math to match the gauge I got….If it weren’t for him I don’t know how long it would have been before I took the next step into design. But he was there, encouraging me to try, and since 2007 I’ve been designing non-stop.”

The observation resonates with the literature on early stage of entrepreneurship that one of the first steps taken by individuals pursuing entrepreneurial opportunities is to speak to a friend about their business ideas and get feedback (Bennett & Chatterji, 2017). Note that the friends or family members in these cases are not necessarily experts in the field, yet future entrepreneurs seem to gain motivation from their feedback and encouragement.

Why do talented knitters begin producing original patterns only after they are encouraged by others? One knitter provided this answer: “It wasn’t until people were commenting on my sweaters and asking where the patterns came from that I decided to write them.” because “I had to get over my shyness and develop self-confidence in my designs.” That is, potential designers often are not certain about the potential market reaction to their ideas or whether they are desirable and valuable to others. They can gain self-confidence by exposing themselves to like-minded community members and getting social feedback. This resonates with another study showing that craft workers show greater willingness to sell their work to an audience who can appreciate it (Ranganathan, 2017). In this context, local community members serve as good audiences who can provide social feedback, mitigating the fear of negative audience reactions in
the market and enhancing self-confidence. The mechanism is supported by another designer who writes:

“For many entrepreneurs, I think the biggest personal challenge is believing in yourself—that what you are creating is something that is desired and valued by others. Loving an idea and creating a marketable product (which is what the business of designing is all about) are not always the same thing. Taking a design from idea to finished pattern takes a lot of investment in energy, money and time, and there is no guarantee that your idea is a good one until the end of the process.”

This observation is consistent with prior studies that have indicated the importance of learning about one’s self in making economic actions and improving job match (Jovanovic, 1979). In a more recent study on nascent entrepreneurs, Howell (2018) show that venture competitions are useful in most part for providing peer feedback.

This observation also supports the particular role of social capital in encouraging individuals to take economic opportunities (Putnam, 2000). For example, an individual is more likely to participate in stock market when they are more sociable, i.e., interacting with their neighbors or attending church (Hong et al., 2004). Also, owner-managers of young firms may achieve higher performances when they join local networks and have regular offline meetings with other members (Cai & Szeidl, 2017). And Zuckerman and Sgourev (2006) documented that the perceived benefit of peers in such relationships is not only to learn from each other but also to augment motivation and raise aspiration levels. Recent studies on the geographic spillover of entrepreneurship also describe a similar social processes by which local peers shape aspiration level and increase the social attractiveness of entrepreneurship (Giannetti & Simonov 2009; Sorenson 2017; Sorenson & Audia 2000).
IV. QUANTITATIVE EVIDENCE

The previous section suggests that peer feedback spurs knitters to pursue entrepreneurial opportunities. This raises the question of whether it is possible to identify the effect of knitters’ encounters with fellow knitters on their entrepreneurial transitions. To that end, I now examine whether the encounters with fellow knitters indeed increases the rate of transition to entrepreneurship.

4.1. Joining SnB Groups

The resurgence of knitting in the United States began with the *New York Times* best-selling book, *Stitch 'N Bitch*, (2003) by Debbie Stoller, a woman who founded a “SnB” group in New York City’s East Village in 1999. Thousands of local SnB groups subsequently were created in the US. In general, SnB groups share these characteristics: (a) the meetings are free and open to everyone who wants to join, (b) the purposes of the meetings are primarily for social interaction, and (c) members are strictly local.

Among the groups listed in Ravelry, 3,000 are categorized as SnB groups and provide information about their meet-ups. In general, SnBs declare their location (e.g., the “South End,” “Jamaica Plain”), meeting place (e.g., “Panera,” “Starbucks”), and an optional characteristic such as religion, profession (e.g., nurses, graduate students, moms), drink preference (e.g., knitting over beer, wine, coffee), and meeting time (e.g., knit night, Sunday morning meet-up). This Ravelry group membership data\(^4\) shows that 71,900 unique Ravelry users belong to at least one

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\(^4\) The membership data do not tell whether a specific knitter attended the meet-up, but as long as the main purpose of the Ravelry group is to organize and schedule the meet-ups and to communicate between group members, knitters have little or no incentive to join the group if they are not going to appear at the meet-ups. Even if they have never been present at an actual meeting, joining indicates their “intent to join the SnB” or their intent to socialize with other knitters.
SnB group in the United States. On average, Ravelry users are associated with 1.61 local SnB groups. The median size of SnB groups at age one is 13 members, and full size distribution at the end of the group’s first year is illustrated in Figure 1.

—Figure 1 goes about here—

4.2. Empirical Strategy

I use observational data of knitters’ SnB membership and consider a knitter’s joining a group to be a shock to a knitter’s potential encounters with fellow knitters. A challenge for this approach is that knitters may seek to join SnB groups because they seek to become entrepreneurs. A review of the qualitative data suggests that this is generally unlikely since this is rarely cited as a reason for joining SnB groups, which are framed primarily in social terms.

Nevertheless, it is important to address this endogeneity analytically. To do so, I constitute a counter-factual control group of knitters who could have, but did not, join the group using extensive observed characteristics of knitters including the knitters’ locations. Then I provide evidence that the difference in the probability of entrepreneurial transition between treated and control knitters appears only after the treated knitters joined a SnB group. The evidence is shown in Figure 2 and provides an ex-post empirical justification for the construction of the control group for the difference-in-difference analysis (Azoulay, Furman, Krieger, & Murray, 2015; Azoulay, Stuart, & Wang, 2014).

—Figure 2 goes about here—
Specifically, the control group is constructed using coarsened exact matching (Iacus, King, & Porro, 2011) with the knitter’s location at the state level,⁵ quarter when the knitter joined Ravelry, and knitting experience variables by the (counter-factual) time of group joining. They include the level of general experience, technical experience, market experience, repeated applications, disobedient applications, and whether the knitter joined the editors’ group. The experience variables are measured by the time they (counter-factually) joined the group (previous quarter to the quarter they joined the group). Also, I excluded knitters who released their original patterns no later than the fourth quarter after they joined Ravelry. This condition necessarily excludes all knitters who released a pattern in 2007, the year Ravelry was launched, and it allows me to observe at least three quarters of a knitter’s activity before her entrepreneurial transition.

After matching on these variables, I dropped controls that do not minimize the sum of squared differences between treated and control groups by the number of projects. Then I randomly selected one observation per strata for 1:1 matching. The final sample for the difference-in-difference analysis consists of 14,145 knitters who joined at least one SnB group during the observation period, and 14,145 control knitters. The descriptive statistics of treated knitters and control knitters is described in Table 2.

—Table 2 goes about here—

To estimate the effect of knitter i joining her local group in time t, I use a linear probability model with individual fixed effects as below:

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⁵ Knitters without location information are omitted here. Knitters from Puerto Rico are also excluded because no knitters from Puerto Rico in the sample became entrepreneurs during my observation period.
E[TRANS_{it}|X_{it}] = \beta_0 + \beta_1 SnB_{it} + f(AGE_{it}) + \delta_t + \gamma_i

where TRANS denotes whether the knitter made the entrepreneurial transition (i.e., became a designer who sells her original patterns), SnB is the indicator variable that takes 1 at the quarter she joins the local SnB group, f(AGE) indicates a function of the knitter's tenure at Ravelry, \delta_t corresponds to a set of indicator variables for each quarter, and \gamma_i denotes the individual fixed effect.

4.3. Results: The Effect of Joining a Local Meeting

Table 3 shows the results of the difference-in-difference analysis. Model 1 suggests that when a knitter joins her local SnB group, her likelihood of becoming a designer increases by 0.64 percentage points. Since the likelihood of becoming a designer is as low as 2.4%, the effect can be interpreted as a 26% increase in the probability of transition. Models 2 and 3 test the effects of a knitter joining her local SnB group on the transition to entrepreneurship. Model 2 shows that when a knitter joins the group, her likelihood of becoming an entrepreneur (a designer who sells her patterns) increases by 0.23 percentage points, meaning a 25% increase in the probability of entrepreneurial transition. Joining the group also increases the probability of entrepreneurial transition after the knitter became a designer. Model 3 suggests that among a subset of knitters who became designers, joining a SnB group increases the probability to charge prices for their patterns by 13%.

---Table 3 goes about here---

4.4. Results: The Heterogeneous Effect of Joining a Local Meeting

To further examine the mechanism of the SnB effect, I turn to the heterogeneous effect among knitters by their knowledge and experiences. First, I examine whether the effect of
joining a local SnB group remains the same for creative knitters who already have designing experience and the necessary skills for transition. As shown in Table 4, the effect of joining a SnB group increases for creative knitters.

—Table 4 goes about here—

Second, I constructed a measure of entrepreneurial human capital for knitters and test whether the effect of joining a local group differs by the level of human capital the user acquired. To operationalize the level of human capital, I estimate the knitters’ predicted probability at one quarter prior to their group membership. The predicted probability is estimated by logit regression including the number of projects made, proportion of repeating projects, number of different project categories explored, number of techniques experienced, voluntary editor status, degree of following yarn suggestions, completeness of yarn information, tenure in Ravelry, and quarter effect. Figure 3 shows that the higher the level of human capital, the larger the effect of joining local groups.

—Figure 3 goes about here—

The quantitative evidence agrees with the mechanism of revealing and encouraging suggested in the qualitative evidence. First, the encouragement effect should be stronger for those who have high levels of skills. Offline in-person interaction allows people to observe each other’s skills in detail, so unlike the education effect, this effect should be the most salient among those with the highest level of entrepreneurial capital. Second, the effect of social encouragement should be stronger for those who have already generated ideas. In-person interaction allows people to observe not only the process of creating an original project but also a set of finished
results. Therefore, the experiences as creative knitters will magnify the encouragement effect within the knitters’ social groups.

4.5. Robustness and Alternative Mechanisms

While the main purpose of a knitting group is to provide opportunities for emotional support and socializing, we can expect possible knowledge transfer as the members of a group knit together and share information about their knitting experiences. Therefore, an alternative explanation for the SnB group effect could be that members of the group learn specific skills (e.g., pattern writing tools) that facilitate their transition to entrepreneurship. One way to investigate this mechanism is to test whether the effect increases when the group includes more designers with greater knowledge. Table 5 tests this effect and shows that the effect of joining a group increases if the group has more designers (Model 2) by the time a knitter joins the group, shows a higher ratio of designers to the total number of members (Model 3), or includes star designers—defined as those who have at least one pattern with more than 300 project applications (Model 4). Therefore, the results support that knitters can learn from designers in the group. However, and more importantly, it is notable that the main effect of joining the group remains very strong and significant even when there are no designers in the group. Therefore, a strong main effect of encouraging and revealing talent seems to persist in addition to the learning effect, which varies by the composition of the group.

—Table 5 goes about here—

V. CONCLUSION AND DISCUSSION

This study examines how social capital facilitates entrepreneurial transitions of users. Using a unique setting of knitting hobbyists where only a minority transition to designers while
most remain as users of designs, the study first shows that many who have entrepreneurial human capital—creative knitters—do not become designers who produce patterns. A qualitative study suggests that the critical factor enabling some creative knitters to transition to designers is the feedback and encouragement they receive from fellow knitters and friends. Based on this observation, I quantitatively test the effect of knitters’ encounters with their peers on their transitions to becoming designers. With a carefully matched sample, difference-in-difference analysis verifies that the participation in an offline local networking group increases the likelihood of transition by 25%.

Furthermore, the results suggest that the social capital effect is largest among those with entrepreneurial human capital, as social capital complements human capital in knitters’ transition to designers. When the role of social capital is to provide access to information and resources, social capital allows actors to compensate for their lack of human capital. However, as suggested by the qualitative evidence, the role of social capital in my setting is not to educate but to reveal talented individuals and encourage them, the effect should be higher for those who already possess entrepreneurial human capital. The mechanism of revealing and encouraging explains the major difference between my results and other studies on entrepreneurial transition regarding for whom the social capital is the most effective.

This study contributes to the existing literature in two ways. First, it contributes to the literature on the role of social capital in innovation and entrepreneurship by suggesting an understudied mechanism of peer feedback and encouragement. Second, as an extension to the first chapter, the study provides a novel perspective on avocational entrepreneurship and platform-based entrepreneurship. By observing users and their experiences as consumers, we can
better understand why some people create new ideas, tinker with their ideas, and eventually commercialize them with little concern about external forces.

The entrepreneurial transition in this study has two distinct characteristics: (a) a very early stage of entrepreneurship and (b) mostly enabled by the existence of online platforms. On the one hand, having these characteristics may present a generalizability concern. That is, the results and implications of the study might not be applicable to the later stages of entrepreneurship where the transition incurs large investments and commitment. On the other hand, however, having these characteristics presents a clear empirical advantage. Since the platform provides most of resources for the transition and the very early stage of entrepreneurship does not incur heavy investments, the study benefits from the setting that reduces the effect of resources on the transition.

Finally, two distinctive features of the social capital studied here are notable. First, the subjects of my study—knitting hobbyists—are mostly women. I matched knit designers’ first names using a gender-guessing algorithm by GenderChecker.com (Kacperczyk & Marx, 2016) and the GPeters database (Leibbrandt & List, 2014) and found the number of male designers to be extremely low (4%). Therefore, the findings of the study carry an important implication for the study of female entrepreneurship. In this context, the salience of peer feedback and the encouragement effect also resonates with previous literature that entrepreneurship is considered to be more of a male occupation (Dimitriadis, Lee, Ramarajan, & Battilana, 2017; Marini & Brinton, 1984) and women tend to be less self-confident and avoid competition (e.g., Niederle & Vesterlund, 2007). Second, the social encounter studied here specifically engages offline meetings. Since Ravelry provides an excellent platform where knitters can easily communicate with each other and provide feedback, the results that Ravelry users experience a significant
feedback and encouragement effect through physical interactions poses an interesting question about the role of offline interaction in the era of online communities.
REFERENCES


Table 1. Descriptive Comparison between Passive Knitters, Creative Knitters, Designers, and Entrepreneurs

<table>
<thead>
<tr>
<th></th>
<th>Knitters (Users)</th>
<th>Designers (Producers)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Passive Knitters</td>
<td>Creative Knitters</td>
</tr>
<tr>
<td><strong>Definition</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Have at least one knitting project</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Create a project with original design</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Codify their original designs and release as patterns</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Have at least one pattern for sale</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Size of population</strong></td>
<td>376,582 (93.4%)</td>
<td>13,456 (3.3%)</td>
</tr>
<tr>
<td>(Proportion among all users)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Knitting experience</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of projects</td>
<td>8.296 (19.556)</td>
<td>51.672 (62.749)</td>
</tr>
<tr>
<td>Number of different knitting techniques applied</td>
<td>8.553 (8.278)</td>
<td>22.0104 (11.527)</td>
</tr>
<tr>
<td>Number of different product categories explored</td>
<td>2.787 (3.034)</td>
<td>8.131 (5.072)</td>
</tr>
<tr>
<td>Proportion of repeated applications</td>
<td>0.042 (0.106)</td>
<td>0.115 (0.125)</td>
</tr>
<tr>
<td>Proportion of disobedient applications</td>
<td>0.215 (0.378)</td>
<td>0.658 (0.352)</td>
</tr>
<tr>
<td>Age at Ravelry</td>
<td>4.122 (1.979)</td>
<td>4.465 (2.143)</td>
</tr>
</tbody>
</table>

Note: All groups are mutually exclusive. Passive knitters are neither creative knitters nor designers. Creative knitters include those who have at least one creative project that incorporates other patterns, but who do not produce a pattern until the end of observation period, 2014Q4. Creative knitters who transitioned to become designers were included as designers, and designers who released a pattern for sale were included as selling designers. Established designers who began designing before or right after joining Ravelry are excluded. All knitting experience variables are measured at the end of observation period, 2014Q4, and the standard deviation is in parentheses.
Table 2. Post-Matching Descriptive Statistics for Knitters who Joined SnB Groups and their Controls

<table>
<thead>
<tr>
<th></th>
<th>Treated (N=14,145)</th>
<th>Control (N=14,145)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (SD)</td>
<td>Min</td>
</tr>
<tr>
<td>Quarter joined (195=2008Q4)</td>
<td>195.7 (5.092)</td>
<td>189</td>
</tr>
<tr>
<td>Editor status (1 if they became voluntary editor)</td>
<td>0.001 (0.027)</td>
<td>0</td>
</tr>
<tr>
<td>Number of projects</td>
<td>5.462 (12.998)</td>
<td>0</td>
</tr>
<tr>
<td>Number of different knitting techniques applied</td>
<td>6.616 (8.477)</td>
<td>0</td>
</tr>
<tr>
<td>Number of different product categories explored</td>
<td>2.080 (2.926)</td>
<td>0</td>
</tr>
<tr>
<td>Proportion of repeated applications</td>
<td>0.019 (0.061)</td>
<td>0</td>
</tr>
<tr>
<td>Proportion of disobedient applications</td>
<td>0.215 (0.387)</td>
<td>0</td>
</tr>
<tr>
<td>Completeness of yarn information</td>
<td>0.087 (0.180)</td>
<td>0</td>
</tr>
<tr>
<td>Creative knitters</td>
<td>0.030 (0.170)</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: The control group is constructed using coarsened exact matching with the knitter’s location at the state level, quarter when the knitter joined Ravelry, and knitting experience variables by the (counterfactual) time of group joining. They include the level of general experience, technical experience, market experience, repeated applications, disobedient applications, and whether the knitter joined the editors’ group. The variables are measured by the time they (counter-factually) joined the group (previous quarter to the quarter they joined the group). After matching on these variables, I dropped controls that do not minimize the sum of squared differences between treated and control groups by the number of projects. Then I randomly selected one observation per strata for 1:1 matching.
Table 3. Effects of Joining Local Groups on Entrepreneurial Transitions

<table>
<thead>
<tr>
<th></th>
<th>[1]</th>
<th>[2]</th>
<th>[3]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Transitions from Users to Designers</td>
<td>Transitions from Users to Entrepreneurs</td>
<td>Transitions from Designers to Entrepreneurs</td>
</tr>
<tr>
<td>Joined SnB Group Ever</td>
<td>0.0064***</td>
<td>0.0023***</td>
<td>0.0507***</td>
</tr>
<tr>
<td>(0.0003)</td>
<td>(0.0017)</td>
<td>(0.0058)</td>
<td></td>
</tr>
<tr>
<td>Transition Rate</td>
<td>0.0242</td>
<td>0.0093</td>
<td>0.3833</td>
</tr>
<tr>
<td>Pseudo R Squared</td>
<td>0.0024</td>
<td>0.0009</td>
<td>0.0298</td>
</tr>
<tr>
<td>N individuals</td>
<td>28,290</td>
<td>28,290</td>
<td>784</td>
</tr>
<tr>
<td>N observations</td>
<td>678,749</td>
<td>678,749</td>
<td>11,320</td>
</tr>
</tbody>
</table>

Note: Transition rates indicate the proportion of knitters who became designers [1] or entrepreneurs [2] by the end of 2014. Unit of analysis is knitter-quarter, and dependent variable is whether the knitter made the transition. Estimates are from linear probability model with individual knitter fixed effect. Robust standard errors are in parentheses, clustered around each knitter. Twenty-nine indicator variables for each quarter and 8 indicator variables for the knitter’s tenure (by year) at Ravelry are included in the model. Established designers who published a pattern before Ravelry became available are excluded. Both control group and treated group are non-designers at the time they joined the group. *p<0.10, **p<0.05, ***p<0.01
Table 4. Interaction between the SnB Group Effect and Creative Knitters

<table>
<thead>
<tr>
<th></th>
<th>All Knitters</th>
<th>Creative knitters</th>
<th>Non-creative knitters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Joined SnB Group Ever</td>
<td>0.0023***</td>
<td>0.0031***</td>
<td>0.0023***</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0012)</td>
<td>(0.0002)</td>
</tr>
<tr>
<td>Transition Rate</td>
<td>0.0118</td>
<td>0.0167</td>
<td>0.0117</td>
</tr>
<tr>
<td>Pseudo R Squared</td>
<td>0.0009</td>
<td>0.0026</td>
<td>0.0009</td>
</tr>
<tr>
<td>N individuals</td>
<td>28,290</td>
<td>836</td>
<td>27,454</td>
</tr>
<tr>
<td>N observations</td>
<td>678,749</td>
<td>19,170</td>
<td>659,579</td>
</tr>
</tbody>
</table>

Note: Transition rates indicate the proportion of knitters who became designers by the end of 2014. Unit of analysis is knitter-quarter, and dependent variable is whether the knitter transitioned to become an entrepreneur. Estimates are from linear probability model with individual knitter fixed effects. Robust standard errors are in parentheses, clustered around each knitter. Twenty-nine indicator variables for each quarter and 8 indicator variables for the knitter’s tenure (by year) at Ravelry are included in the model. Established designers who published a pattern before Ravelry became available are excluded. Both control group and treated group are non-designers at the time they joined the group. *p<0.10, **p<0.05, ***p<0.01
Table 5. Interaction between the SnB Group Effect and Group Characteristics

<table>
<thead>
<tr>
<th></th>
<th>[1]</th>
<th>[2]</th>
<th>[3]</th>
<th>[4]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Joined SnB Group Ever</td>
<td>0.0064***</td>
<td>0.0054***</td>
<td>0.0056***</td>
<td>0.0056***</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0005)</td>
<td>(0.0005)</td>
<td>(0.0004)</td>
</tr>
<tr>
<td>SnB Joining X N Designers</td>
<td></td>
<td></td>
<td>0.0004**</td>
<td></td>
</tr>
<tr>
<td>in the groups, logged</td>
<td></td>
<td></td>
<td>(0.0002)</td>
<td></td>
</tr>
<tr>
<td>SnB Joining X Ratio of Designers</td>
<td></td>
<td></td>
<td>0.0079**</td>
<td></td>
</tr>
<tr>
<td>(N designers / N members)</td>
<td></td>
<td></td>
<td>(0.0040)</td>
<td></td>
</tr>
<tr>
<td>SnB Joining X Potential Contact with Star Designers</td>
<td></td>
<td></td>
<td>0.0013***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.0005)</td>
<td></td>
</tr>
<tr>
<td>N individuals</td>
<td>28,290</td>
<td>28,290</td>
<td>28,290</td>
<td>28,290</td>
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Note: Transition rates indicate the proportion of knitters who became designers by the end of 2014. Unit of analysis is knitter-quarter, and dependent variable is whether the knitter transitioned to become an entrepreneur. Estimates are from linear probability model with individual knitter fixed effects. Robust standard errors are in parentheses, clustered around each knitter. Twenty-nine indicator variables for each quarter and 8 indicator variables for the knitter's tenure (by year) at Ravelry are included in the model. Established designers who published a pattern before Ravelry became available are excluded. Both control group and treated group are non-designers at the time they joined the group. *p<0.10, **p<0.05, ***p<0.01
Figure 1. Size Distribution of SnB Groups

Note: SnB group size is measured at the end of 12 months after the group was founded. The median size of groups at age one is 13, and the mean size at age one is 23.22. Groups with less than 4 members by December 2014—the end of the observation period—are manually checked and omitted unless they provide clear records of actual meetings and interactions.
Figure 2. Dynamics of the SnB Joining Effect on Entrepreneurial Transitions

Note. The blue dots in the above plot correspond to coefficient estimates from a linear probability model with individual fixed effects (the coefficient of Table 3, column [2]) in which the probability of knitters to become designers is regressed onto quarter effects, knitters' tenure in the community effects, as well as 17 interaction terms between treatment status and the number of quarters until they first joined a local SnB group. The baseline of the interaction effect is 6 or more quarters before the treatment. The 95% confidence intervals around these estimates are shaded in light blue.
Figure 3. Interaction between the SnB Group Effect and Human Capital

Note. The blue dots in the above plot correspond to coefficient estimates from a linear probability model with individual fixed effects in which the probability of knitters to become entrepreneurs is regressed onto quarter effects, knitters' tenure in the community effects, as well as 10 interaction terms between treatment status and indicator variables for each decile of the predicted probability of a knitter's transition to an entrepreneur. The predicted probability is estimated at one quarter prior to joining a group, and by logit regression onto the number of projects made, proportion of repeated projects, number of different project categories explored, number of techniques experienced, voluntary editor status, degree of following yarn suggestions, completeness of yarn information, age in Ravelry, and quarter effect. The 95% confidence intervals around these estimates are shaded in light blue.
Chapter 3

Never Really One of Us:

Commitment-based Typecasting among Knit Designers

I. INTRODUCTION

It is common for individuals to feel that they have become “typecast” by audiences in the sense that they are assigned to a narrower range of social categories than is reflected by their talents or potential. Following Faulkner (1983), research has demonstrated that becoming typecast is both blessing and curse for a novice in a particular domain. Especially where credentials are unimportant and many candidates compete to gain entry (see Zuckerman, Kim, Ukanwa, & Von Rittmann, 2003; cf., Ferguson & Hasan 2013; Merluzzi & Phillips 2016), the advantages of becoming typecast loom large. To be typecast is to achieve at least some kind of recognition. But once one has gained such a toehold, the limitations of typecasting become more salient. Since audiences screen candidates on the basis of their fitness for a particular purpose (Zuckerman 2016), becoming typecast in one category, or in highly related categories (Leung 2014), tends to hinder recognition for different purposes. To gain recognition in one category is to lower the likelihood one will be considered for membership in unrelated categories.

A straightforward explanation is rooted in evaluators’ attempts to infer skill from the set of opportunities that a candidate has been offered in the past (Zuckerman et al., 2003). As long as producers with greater skill in category X obtain chances to perform in X, it will make sense for evaluators to assume that candidates who have specialized in X are skilled in X, and those who have not specialized in X are not skilled in X. Moreover, insofar as category Y requires skills

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6 This paper is coauthored with Pierre Azoulay and Ezra W. Zuckerman.
that are different from those needed for X, it makes sense for audiences to apply the “the
typecasting rule of thumb” (Zuckerman et al., 2003) and infer those who have specialized in Y
do not have the skills needed for X.

But while this skills-based reasoning is sufficient to generate the trade-offs in achieving
recognition, there is reason to think that it is not necessary. In particular, it is intriguing to
consider cases where producers who demonstrate excellence in multiple categories nonetheless
struggle to gain recognition as fit for membership in one or more of those categories. A well-
known case is that of Bo Jackson, a man who is often named as one of the greatest American
athletes of the twentieth century and who was named an all-star in both Major League Baseball
and the National Football League. Notably, Jackson was the subject of a marketing campaign for
Nike under the theme “Bo knows X,” with the advertisements portraying him as a star in
baseball and football, as well as a myriad other cultural and athletic activities. But despite being
famous for being talented in both baseball and football, and indeed being even better at football,
Jackson was denigrated by many football fans. The problem was not one of capability but of
commitment. Since professional baseball season ends after football season begins, at the outset of
his professional career, Jackson had to join his football team several games into the season.
Moreover, while he first maintained that he was fully focused on each during their respective
seasons, football fans became furious when he commented that “whatever comes after baseball
season is a hobby (New York Times, 1987).” This was not just a momentary reaction: many
football fans never forgave Jackson for not treating the sport with the respect they felt it was due
(cf., Hahl 2016). He was rejected as a football player despite being one of the best players of his
generation.
The case of Bo Jackson is singular in various ways, but it hints at a different basis for
typecasting, whereby a candidate is screened out of category X not because her participation in
category Y suggest she lacks the necessary skills for X but because it suggests she is not
committed to category Y. This possibility is in line with several studies in economic sociology.
For instance, Phillips, Turco, and Zuckerman (2013) document how the clients of corporate law
firms penalize such firms that diversify into personal injury law not because they perceive the
firms to be less capable but because they are perceived to be less committed. Similarly, Frake
(2016) recently provided evidence supporting Carroll and Swaminathan’s (2000) observation
that consumers penalize a microbrew when it is produced by a “macrobrewer” even when there
is no difference in quality; the issue again appears to be the lack of commitment that the
macrobrewer appears to have to the microbrew market. And when cultural performers “break
out” of their niches and to become mass market stars, the original niche audience often reacts
negatively to the apparent betrayal (Peterson 1997; cf., Zuckerman & Kim 2003). More
generally, insofar as consumers care not only about whether a producer is capable of performing
at a sufficiently high level but whether she is committed to serving the consumer (see Hahl 2016;
Hahl & Ha 2016), there may be a second basis for typecasting, what we call “commitment-based
typecasting.”

The main objective of this paper is to put the phenomenon of commitment-based
typecasting on strong theoretical and empirical footing. The key theoretical insight is that
commitment-based typecasting has two characteristic features that reflect what is distinctive of
commitment-based evaluation more generally: asymmetry in audience valuation and
retrospective revaluation. The particular context for commitment-based typecasting is a social
domain riven by an “identity divide”—where there are multiple audiences for a given set of
performers and the members of at least one of those audiences (e.g., country music devotees; football fans) regard their needs as conflicting with those of other audiences. In such a contest, we can expect asymmetric reactions to updated information about a candidate’s commitment, such as Bo Jackson’s statement about football being a “hobby” or a singer who straddled the country/pop boundary accepting recognition as a pop star. Prior to that moment of public recognition—what we call an identity shock—each audience might have regarded the performer as belonging to their category. But once this shock occurs, it should have an asymmetric effect: one audience should now react negatively and screen out the performer as uncommitted to it whereas the other audience updates its prior beliefs little if at all. In addition, this negative Bayesian updating process has retrospective implications. Prior to the shock, the performer’s work had enjoyed the benefit of the doubt since the default is to presume that any performer who can exceed the quality threshold for that category is committed to that category’s audience. But now it appears that she was always committed to the rival audience/category. The “betrayed” audience can be thus expected to place less value on performances that it had previously assessed as being meritorious even though these performances are fixed in time and thus did not change in quality: Fool me once, shame on you; fool me twice, shame on me.

In the next section, we elaborate on our theoretical framework. We then apply it to the domain of knitting. The knitting scene has recently experienced an intriguing social movement of avant-garde knitters who seek to transform the culture of knitting (see Fields [2014]), and this has engendered an identity divide in the knitting world between avant-garde and traditional knitters. As discussed below, members of each audience have tended to portray a sharp difference between them based on objective quality. But as in many cases, the boundary between the two categories is often quite blurry in that some designs can be recognized as being of good
quality by both audiences, and novice designers can potentially be regarded by each audience as committed to it. Our framework provides us a way of demonstrating the importance of commitment-based typecasting in such a context. In particular, we exploit the natural experiment engendered by the “identity shock” experienced by the knitting audience when a novice knitter receives her first publication in either an avant-garde or a traditional knitting magazine, thus revealing her to be committed to one side of the identity divide rather than the other. Finally, to test our prediction of retrospective, asymmetric revaluation, we adopt the approach of Azoulay and colleagues (Azoulay, Stuart, & Wang, 2014; Azoulay, Bonatti, & Krieger, 2015), and analyze the effect of a producer’s identity shock on the demand trajectory of the products released before the shock. This research design has two main advantages. First, because the demand change is tracked in a product fixed-effects framework, the effect of producers’ capability is fully controlled for. Second, the analysis restricts the sample to products designed before the identity shock, which allows us to rule out the potential effect of change in the producer’s actual commitment.

II. THEORY

2.1. The Demand for Commitment in Markets

An important line of recent research documents that market audiences often seem to care about the commitments of producers to a degree that cannot be reduced to the quality of goods and services. For example, Vasi, Rynes, Nielsen, and Li (2015) show that some consumers of farmers market proudly declare that they shop at farmers’ markets to "support local farmers," regardless of product quality; Verheel, Khessina, and Dobrev (2015) document how consumers infer signals of commitment from the producer’s organizational form (see also Ha 2016) and product names in a manner that is unrelated to the attempt to infer product quality; and Frake
provides strong evidence for Carroll and Swaminathan’s (2000) observation that microbrew consumers discriminate against major breweries, and that this preference cannot be explained by perceptions of quality.

Not only is there good evidence that audiences may demand commitment independent of quality, the key contextual conditions for such demand has been explicated as well. In particular, Phillips, Turco, and Zuckerman (2013: pp. 1045-6) observe that for an evaluator/consumer to care about commitment independent of quality, it is necessary that the exchange be not a one-time act but an “affiliation” or ongoing public relationship. The key question is whether one will be asked to account for one’s affiliations with a producer in the future by an audience that uses such affiliations as basis for judging one’s own commitments (especially when our own quality is difficult to observe). If the answer is yes, it is rational to avoid the candidate who looks less committed even if there is no difference in quality (cf., Correll, Ridgeway, Zuckerman, Jordan-Bloch, & Jank, 2017).

As Phillips et al (ibid.) observe, this contextual feature is present in two broad types of settings: (a) in markets for representation (e.g., professional service firms such as corporations retention of law firms [Phillips et al., 2013] and behavioral health clinicians referrals to healthcare clinics [Hahl & Ha 2016]); and (b) in consumer markets where consumers use the products to signal their social identities. In each of these and related settings, there tend to be multiple distinct social identities, some of which may be defined in opposition to others. Such opposition is expressed in that membership and status within the community associated with the identity is determined based on whether an individual appears committed to it rather than its rivals. In short, each of the communities is “greedy” in demanding loyalty to it. In many cases, one of these social identities emerges via the efforts of a social movement that emerges to oppose
an established community, and may thus be especially greedy in rejecting any affiliation with the other side. Examples of such dynamics come from French cuisine (Rao, Monin, & Durand, 2005), musical genres (Lena & Peterson 2008), feature films (Zuckerman & Kim 2003), bookstores (Miller, 2008), and wine (Negro, Hannan, & Rao 2011; Negro & Leung 2013). Social movements are not necessary to induce this demand for loyalty though, and it need not be asymmetric. For example, had Bo Jackson shown greater commitment to football than to baseball, baseball fans likely would have rejected him just as football fans did in actuality. For commitment-based typecasting to occur, all that seems necessary is the presence of a social divide and a reason for each community to demand commitment to their side as a prerequisite for conferring membership and status.

2.2. The Challenge

While this basic precondition for commitment-based typecasting may be straightforward, more theoretical development is needed in order to understand the underlying dynamics of commitment-based typecasting and to demonstrate its importance relative to skills-based typecasting. The main challenge is that while it may be possible to rule out the possibility that skills-based typecasting is responsible for the denigration of Bo Jackson by football fans, it is generally quite difficult to rule out this alternative because capabilities and commitments are generally endogenous and thus intertwined: producers who are committed to a particular category of product or service tend to invest in developing their capabilities, and more capable producers have stronger incentives to invest in maintaining a desirable market position (see Benjamin & Podolny 1999). Accordingly, while Leung (2014) interprets employers’ avoidance of candidates who range across highly disparate jobs as a form of commitment-based typecasting, it is also possible that employers perceive erratic moves as a sign of lower skills—
either because less talented workers are forced to take whatever jobs they can or because less committed workers forgo the opportunity to hone their skills in a given category. It is not clear that lower commitment *per se* is the issue (nor is it clear the labor markets he studies is one where employers are sensitive to the reactions of a greedy community). Relatedly, while Frake (2016) demonstrates a decline in microbrew customer’s appreciation for a craft beer when the brewery is purchased by a corporate owner, and he shows that this decline cannot be explained by declines in the rating of the beer, this negative reaction might reflect the raters’ *changed expectation about the future* quality of the beer. After all, ratings are meant to provide guidance about the future and a rater’s reputation is on the line to provide such guidance.

2.3. Proposed Approach

To complement these studies then and flesh out how commitment-based typecasting works, we develop an approach based on a key observation about how inferences about commitment differ from inferences about skill. In particular, inferences about commitment in the context of competing social identities are *retrospective* and *asymmetric* in ways that inferences about skill are not.

Before elaborating on the underlying logic, several cases help capture the intuition. First, consider again the case of Bo Jackson. Upon learning of his betrayal, football fans regarded his *past performances* as tarnished, but baseball fans did not reward him to offset the same degree. Consider also the dynamics in the case of divorcing couples, as documented by Hopper (1993, 2001; cf., Vaughan 1986). Even if both spouses are unhappy, it is typical for one of the spouses to get the idea of divorce and to share with the other his/her realization that they had both been “going through the motions” for some time. The other spouse, who has typically not yet come to this realization, typically reacts very negatively and argues that s/he had been sincerely
committed to the relationship and apparently the other had been faking his/her commitment. Thus we again have a case of retrospective devaluation of past performances, and it is asymmetric. Note finally how scandals—"disruptive publicity of transgression" (Adut, 2005)—also involve retrospective revaluation and tend to ruin reputations, to the point that all prior performances become suspect. Thus, Oscar Wilde’s work became taboo once the scandal of his homosexuality broke out in Victorian England (Adut, 2005). And when malicious intent is verified, the retraction of a fraudulent research article not only endangers its author’s future career, but also lowers appreciation for prior studies (Lu, Jin, Uzzi, & Jones, 2013; Azoulay, Furman, Krieger, & Murray, 2015; Azoulay et al., 2015). However, there is not necessarily asymmetry in such cases of scandal, whereby a second audience retains a positive valuation of the actor. That is because such transgressions are violations of ethical norms, whereby the actor is revealed to have wanton disregard a particular community and its values, whereas the first set of transgressions are violations of loyalty norms, whereby the actor is revealed to be committed to a rival community rather than the focal one (Phillips et al., 2013: pp1050-1).

Thus let us now clarify how and why new information about an actor’s commitment relative to an identity divide has a retrospective, asymmetric effect on valuations. Two more specific observations are key. First, even though two audiences may define themselves in opposition to one another, there is often considerable overlap in how two opposing audiences define quality. This is to be expected in some sense; if they had completely disjoint tastes, they would be different markets and there would be nothing to disagree about. Accordingly, both microbrews and macrobrews are evaluated on the basis of “aroma,” “taste,” “appearance,” and “palate”). Consider also what happens if an erstwhile country singer “crosses over” and becomes a major pop star. In such cases, country music devotees have often reacted much in the manner
of football fans to Bo Jackson. But the very fact that such instances of cross-over occur reflect the similarity in quality standards among the two audiences. Part of the negative reaction seems to reflect the horror at discovering that their tastes are not so unusual after all.

Let us then assume the existence of a pair of opposed audiences with some overlap in quality standards. And now consider a second observation: performance figures directly in inferences of skill, but indirectly in inferences of commitment. To be more specific, assessments of skill are generally monotonic in demonstrated performance. As long as there is no question as to the integrity of a performance—e.g., we know that the athlete did not engage in doping, or that the science did not fudge her data or plagiarize someone else’s work—an actor who achieves at a higher level relative to an audience’s quality standards should elicit a higher assessment of his skills.

Now consider how commitment is inferred from performance and from a second indicator, decisions to publicly affiliate with one community or another. All things equal, assessments of commitment will also be monotonic in performance—i.e., since it takes a greater expenditure of effort to achieve higher performance, evaluators can assume that higher performance signals higher commitment. However, whereas no actor can achieve high (validated) performance without great skill, it is possible for an actor to achieve high performance despite a lack of commitment to the audience. In particular, this will be true under our assumption that there is overlap in the quality standards used by two audiences, and when the performer is a novice such that she has yet to be publicly associated with either community. Under such conditions, each audience may see the same set of performances, assess that they are good by its standards, and thereby infer that the performer is committed to its community. After
all, it takes an investment of time and resources to learn such quality standards and hone the
skills needed to meet them.

But matters will change if the erstwhile novice performer takes an action that publicly
affiliates herself with one side of this divide. Such an affiliation is more diagnostic than
performance; if a performer chooses to publicly affiliate with audience X rather than audience Y,
it implies that the performer has effectively invested in X such that her reputation rises and falls
with the fate of the X community. At that point, community Y will decide that it was mistaken
about the performer’s commitment to its community, thus effecting a sharp reversal. By contrast,
community Y will merely have confirmation of its initial assessment, thus leading to marginal if
any upward movement in its assessment.

Figure 1 illustrates the logic of this process. We suppose here a novice performer who
elicits a monotonically increasing assessment of his commitment to either audience X or
audience Y based on performances that meet their respective quality thresholds. We have
assumed that some performances meet X’s threshold, some meet Y’s threshold, and some meet
both audience’s thresholds. This continues until there is an “identity shock”—a public event that
affiliates the performer with audience Y in a manner that reflects the choice of the performer. At
that point, relatively changes in the audience X’s assessment of the performer’s commitment to
it. By contrast, community Y’s now regards the performer as uncommitted to it, and he is
presumably rejected. Moreover, insofar as the members of each community will reject
performances by performer’s that are committed to the other audience, they will reject even the
past performances that they previously regarded favorably. Put differently, the revealed identity
becomes a new interpretive scheme, and consumers not only apply that scheme to current and
future performances (Smith, 2011), they also make sense of her entire career—including past behaviors—according to the new interpretive scheme of identity.

— Figure 1 goes about here—

2.4. Hypotheses

We conclude our theoretical discussion by postulating formal hypotheses. We will articulate them in the context of the domain we analyze in this paper—the contemporary knitting scene. As we discuss below, this is an apt setting for validating our theory of commitment-based typecasting because it has recently witnessed an intriguing social movement of avant-garde knitters who seek to transform the culture of knitting by opposing the community of traditional knitters (see Fields [2014] and below). As in the other cases reviewed above, membership of the performer in one or the other community signals its commitment to that community, and its opposition to the other.

Based on our theory, we will focus on what happens when an “identity shock”—the first publication of a novice knitter’s designs in either an avant-garde or a traditional magazine—occurs. Since it is a choice to publish in a magazine, it reflects a decision to publicly affiliate with one of the communities rather than the other. At the same time, the quality standards of the two communities overlap to a significant extent. This creates the conditions necessary to test the following hypotheses:

*Hypothesis 1. When a previously-unpublished knitter publishes in a traditional magazine, the demand for the knitter’s earlier designs will (a) decrease among avant-garde knitters; and (b) this decrease will be greater than any increase in demand from traditional knitters.*
Hypothesis 2. When a previously-unpublished knitter publishes in an avant-garde magazine, the demand for the knitter’s earlier designs will (a) decrease among traditional knitters; and (b) this decrease will be greater than any increase in demand from avant-garde knitters.

III. SETTING

To test commitment-based typecasting, we chose the knitting industry. By the early 2000s, an interesting social movement had emerged in the knitting scene. In particular, a group of young knitters emerged and expended significant effort in differentiating themselves from “grandma’s knitting,” thereby reshaping the reputation of knitting more generally, so that it would come to be recognized as a creative hobby (Fields, 2014). Our observation on the knitting scene also supports the existence of an identity contrast among the knitters and the difference in their perceptions on the knitting design by the identity. Therefore, the movement provides a good setting for studying the impact of being typecast among audiences of different identities.

To begin with, it is important to understand the market for knit designs, which comprises two principal roles: designers and knitters. Designers are responsible for designing an original knitting pattern, a recipe for making a particular knitted piece, such as a sweater or a pair of socks. The pattern typically consists of written information about the knitting supplies needed (e.g., yarns, needles), size, and detailed step-by-step text instructions with optional cable charts. Knitters then choose among available designs in the market and follow the directions written in the pattern. In terms of the market for pattern designs, designers are producers whereas knitters are consumers of designs.
The market is commitment-intensive in several aspects. When choosing a pattern, knitters tend to consider not just the product itself, but also the identity of the producer. One knitter noted that “the strongly successful designers are those who a) realize that they are selling themselves as well as their patterns; and therefore b) strongly define their virtual persona.” Knitters also view their consumption of a pattern as an effective endorsement for the designer; as one designer recalled, “I even had a few people tell me they have bought a pattern just to support me.”

The issue of commitment becomes salient when the market observes the existence of competing identities. One compelling description of competing identities in the knitting community is in the field note of Fields (2014). He talked to a member of a young knitters’ group who distanced herself from another group of “standard knitters,” referring to “a bunch of old ladies who meet at the library and talk about their grandkids.” She added that “I’m pretty sure there is no overlap between the two groups.” According to our qualitative analysis, the divergence between the two groups is supported by “generation gap,” “demographics,” and “homophily” codes. One group of consumers, which we call “avant-garde” knitters, are described by the codes “young,” “net-savvy,” “progressive,” and “indie,” while the other group of consumers, which we call “traditional” knitters, are described by the codes “old-school,” “grandma,” “classic,” and “professional.” Since the mid-2000s, the avant-garde group’s activities have been facilitated by the rise of online communities that have served as channels for exchanging unique knitting patterns and fostering relationships among groups of like-minded knitters.

Traditionally, patterns were distributed through local yarn store pamphlets or the magazines of professional publishers and through several prominent magazines, such as Vogue Knitting and Interweave Knit. For novice designers, publication in these magazines has been
considered a big opportunity in their career. One designer described her first publication in a major magazine as “the moment of spotlight,” which earned her “global recognition.” By releasing their design to these mainstream markets, the designers can get more publicity, which usually leads to higher revenue. Another designer said, “if I don’t get into Vogue and Interweave Knits, I will never gain the attention of enough knitters to make money.” Even after online pattern sales became widely available, having a pattern published in either of the two magazines—Vogue Knitting and Interweave Knits—is nonetheless difficult.

Although mainstream magazines can certainly increase a designer’s publicity, not all knitters are fans of popular magazines. A knitter explained that mainstream magazines “regularly produce incredibly boring and shapeless designs that I would never ever knit.” In opposition to mainstream magazines, an online magazine, Knitty.com serves as their own parameter of recognition among avant-garde knitters. Another designer acknowledged the variance in the knitters’ preference for magazines, explaining her preference for avant-garde taste. She said, “I shudder to think of a knitting universe still confined to the boring and frilly parameters of (most) knitting magazines. When Ravelry and Knitty burst onto the scene it was a big relief. Fun! It’s still fun even if a bit messy and crowded.”

The online magazine is as selective as traditional print magazines. While only 1.9% of the designers in our sample from Ravelry (see below for details) have ever published in either of the two major magazine—Vogue Knitting and Interweave Knits—only 1.4% of the designers have ever published in the prestigious web magazine, Knitty.com. For it is selective to be published in these magazines, the publication has a significant impact on a pattern’s popularity. As shown in Table 2, the patterns published in these magazines have significantly higher chances of being adopted and applied by other users, while publication in other magazines have no
significant impact on the chance. Based on the impact of publication in these prominent magazines on the public recognition among knitters, we regard publication as identity shock in knitting communities.

IV. ANALYSIS

4.1. Data

The analysis is based on historical data of Ravelry.com, downloaded on May 5, 2014. Ravelry, the so-called “Facebook of knitters,” has more than 7 million registered users worldwide, and served as a major marketplace for knit patterns since its launch in 2007. As of January 2012, over 30,000 knitting pattern designers are registered and 1.3 million patterns had been sold on Ravelry. In addition to its role as market for patterns, Ravelry serves as a popular platform where ordinary knitters can talk about patterns available and record their own work (“project”) which applies the patterns.

Ravelry provides a compelling research site because of this unique double-layered structure of “patterns” created by “designers,” and “projects” applied by “users” (Figure 2). “Users” include all the knitters who use Ravelry, whereas designers are those who design and share their original patterns with a unique designer identifier. When users upload their knitting projects, they explicitly refer to the pattern design that they are applying, allowing not only researchers but also other users to learn whose pattern is adopted by whom and when. On each designer’s page, users see a list of all the patterns that the designer has uploaded, accompanied by key information on each pattern, including its sample pictures, date of release, and publication sources. The designer data, combined with the user profile data, show when a designer first registered on Ravelry and provide a brief description of her knitting experience and her activity
in the Ravelry community. Among the 26,501 designers who have a unique designer identifier, a user identifier, and at least one pattern design uploaded, we focus on the 12,306 designers who indicated that they were located in the United States.\(^7\)

— Figure 2 goes about here—

**Product: Pattern.** The pattern data consist of 107,231 patterns uploaded by US designers. The data include unique identifiers for the pattern and its designer, the price, the date of the page’s creation and the latest update, the crafting type (crochet/knitting/loom knitting/machine knitting), the category,\(^8\) the original source of publication, and the number of projects that have applied the pattern, which we call “project application” and will explain further below.

**Demand: Project Application.** Project data collected from the project pages in Ravelry.com include information regarding the pattern and yarn used for the project, the date the project was started, pictures of the work (optional), the progress on the work, and the viewership of the project. In the analysis, we omitted projects with missing date information and projects with ambiguous data points, such as projects started before the pattern was created or before Ravelry’s launch in 2007.

— Figure 3 goes about here—

\(^7\) We focus on the US designers because (a) the social movement that constitutes our setting is among US knitters and (b) the hierarchy of magazines is based on the audience in United States.

\(^8\) Category means 67 classifications of the pattern, including clothing such as tops, vests, and coats/jackets; accessories such as bags, hat, and mittens; home products such as decorative objects, coasters, and blankets; toys and hobby accessories such as costumes and softies; pet-related goods; and components such as afghan blocks, buttons, and charts.
Users who create a project on Ravelry make serious commitments to create a project because they are expected not only to work on their own knitted piece but also to create the project page on Ravelry and report the knitting process, which is often accompanied by pictures. Each day, 7,000 new projects are created on Ravelry, and over 9 million finished projects have been listed on the website as of April 8, 2015. As expected, the projects-per-pattern distribution is highly skewed (Figure 3), with a median of 3 and a mean of 23.9 (SD=180). Note further that 21% of patterns do not attract a single project from any user on Ravelry, and 59% of patterns attract fewer than 5 projects. The average number of project applications per designer is also skewed, with a median of 19 and a mean of 273.5 (SD =1,555, max= 84,363). The designer with the highest demand by the aggregate number of projects is Jared Flood, the owner and creative director at Brooklyn Tweed, a knitwear design and yarn company founded in 2007.

One notable characteristic of our project data is that we can identify the user who applies a pattern and the date that she initiates the project. By matching the user ID with the designer ID, we can thus exclude all project applications by the designer herself—a concept equivalent to self-citation in academia—from the total demand. Furthermore, we can capture demand by user subgroups, such as traditional knitters and avant-garde knitters.

Subgroup Demand: Avant-Garde vs. Traditional. To explore different reactions by audience members of different identities, we need to construct two subgroups of audience—traditional and avant-garde. The first challenge here involves defining and operationalizing the two groups as independently as possible from the demand measurement. We used “group” information because Ravelry users often organize online social groups (forums) according to their shared interests. Because group membership is voluntary and open to the public, it constitutes good identifiable information about the users’ interests and inclinations.
Each group on Ravelry has a distinct group name and a couple of introductory paragraphs from which the group’s self-claimed identity can be inferred. We selected seven large groups that declare their identities according to the age of the members (e.g., Knifty Fifties, teens knit & crochet, etc.) or the culture to which their age is related (e.g., grandma's hand, i might like yarn, but i'm not your granny!, etc.). Table 1 illustrates how each group describes its identity and provides the basic descriptive statistics for each group.

— Table 1 goes about here—

The traditional group consists of 2,287 members of four “aged” Ravelry groups, whereas the avant-garde group consists of 3,372 members of three “young” Ravelry groups. Only five members are found in both groups, and they are omitted from the analysis. Because the analysis focuses on knitters who actually apply a pattern and make projects, knitters without project records are also excluded from the data. Approximately half of the members (1,177 traditional knitters and 1,473 avant-garde knitters) appear in our data. The projects applied by each subgroup (traditional—19,399 projects; avant-garde—14,363 projects) constitute only a small part of the total demand and account for approximately 1% of the all projects on Ravelry. Based on the subgroup demand, we compute four demand measures—total demand, demand by avant-garde knitters, demand by traditional knitters, and demand with group label (either traditional or avant-garde). The results suggest that the demand with group label is not different from the total demand.

**Recognition: Publication.** Every pattern notes not only its designer but also its “source,” i.e., the first place where it was published. The source can be published books, magazines, or the designer’s blog. Designers are asked to fill in the name of the original publication source and the time of its publication, (e.g., Vogue Knitting, Winter 2011/12). Users can view the source
information when they shop for patterns, and such an explicit indication of the source makes it possible to observe the influence of public recognition by a specific audience.

Although there are dozens of magazines, the focus of this research is on a handful of magazines with substantial publicity. Among the magazines, two—Vogue Knitting and Interweave Knits—stand out as particularly prestigious among traditional knitters, and Knitty.com among avant-garde knitters. These magazines top the list in several data source (See Appendix. Coding of Pattern Sources for details), and qualitative evidence supports the claim that having published in one of these magazines is a great achievement for a designer. Therefore, we view the publication in Vogue/Interweave as a significant moment—i.e., an “identity shock”—that brings recognition of the designer among traditional knitters, while the publication in Knitty.com similarly raises recognition among avant-garde knitters.

4.2. Descriptive Statistics

The baseline sample contains 107,231 patterns by 12,306 designers. With this full sample, we first examine the general effect of the pattern’s source, using a cross-sectional analysis. The results confirm our earlier observation that designers compete to be published in prominent magazines such as Vogue/Interweave or Knitty.com and that users prefer these patterns.

Table 2 summarizes the results of the cross-sectional analysis. The dependent variable is the total number of projects a pattern attracts up until 2014Q1, when our data were collected. The main variables are source variables, which are classified into seven mutually exclusive categories. The pattern’s age is controlled by a series of indicator variables for 29 quarters from when the pattern was first created. The pattern characteristics and quality are partially controlled by the designer fixed effect, 67 indicator variables for the category fixed effect, and four
indicator variables for the craft-type fixed effect. The first row of the table shows that the pattern attracts significantly more projects when the pattern’s source is one of the two top-tier mainstream magazines, *Vogue Knitting* or *Interweave Knits*. The second row of the table shows that the pattern attracts significantly more projects when the pattern’s source is the prestigious web magazine, *Knitty.com*.

— Table 2 goes about here—

Among these 12,306 designers, 370 (3%) have published in *Vogue* or *Interweave*, and these designers constitute our first “treatment” group—i.e., those who received a mainstream identity shock. Among these 370 designers, we also exclude 133 designers who have published in mainstream magazines but have turned out to be inappropriate as a treatment group because they had already established a mainstream identity before the shock. In particular, the published designers consist of those who 1) had one or more patterns before their first publications in *Vogue/Interweave* and 2) had no major publications, including book publications from prominent publishers (e.g., Interweave Paperbacks), or appearances on television shows before her recognition through the magazines (cross-checked manually). Limiting the scope of published designers secures a clean treatment setting in which to observe the effect of identity shocks because the treatment is redundant for designers who have previously made their names through alternative mainstream media exposure. Our final sample of mainstream designers consists of 237 designers.

Our second treatment group who received an avant-garde identity shock comprises 346 designers who have ever published in *Knitty.com*. By the same process of constituting the first treatment group, we excluded those who 1) had no patterns before their first publications in *Knitty.com* and 2) had any major publications, including book publications from prominent
publishers (e.g., Interweave Paperbacks), or appearances on television shows before her recognition through the magazines (cross-checked manually). Our final sample of avant-garde designers consists of 197 designers.

The remaining unpublished designers constitute our control group, for which justification will be provided later. To identify causal effect by the identity of designers, our analysis targets the pre-treatment patterns of treated designers. Therefore, the treatment group at the pattern level consists of pre-publication patterns by published designers, whereas the control group consists of all the other patterns by unpublished designers. Figure 4 shows the construction of our sample in the pattern level.

— Figure 4 goes about here—

4.3. Statistical Approach

The central challenge of identifying the causal effect of an identity shock in part of any demand shift concerns separating the assessment of quality from the change in the producer’s identity. To net out the unobservable effect of quality, we use two main analytical strategies as follows.

First, we use difference-in-differences (DID) estimation regarding identity shocks as treatments of a natural experiment, whereas the non-treated group constitutes the valid control group. For example, Azoulay et al. (2014) empirically examined the effect of a producer’s status shock (winning a prize) on the trajectory of the producer’s product, and successfully disentangled the pure effect of status from the quality difference accompanied by the status difference. Following Azoulay et al. (2014), this study tries to show the pure identity effect independent of the objective characteristics of the product.
Second, our analysis focuses on the pre-publication patterns of published designers, i.e., the patterns that were previously uploaded to Ravelry before the designers were published in *Vogue/Interweave* or *Knitty.com*. We excluded treated patterns that directly caused the identity shock, as all treated patterns are “born” published, and exhibited no variation in their treatment status. Most magazines, particularly the magazines of interest in this study—*Vogue Knitting*, *Interweave Knits*, and *Knitty.com*, require the submission of a “new to the world” pattern, i.e., one that has not yet been released via other channels, including Ravelry. An additional benefit of limiting the analysis to preexisting patterns is that the quality of the patterns in the dataset could not have been influenced by other attributes connected to the publication. Thus, we can restrict the operative mechanism to changes in the perceptions of identity, as opposed to the potential effect of publication on enhancing the designer’s actual commitment to the patterns created after the identity shock, or any other mechanisms that might potentially influence the designer’s capability and cause the publication or shift in demand accordingly. Because no new information exists about the product’s quality since its upload on Ravelry, the treatment effect will be purely about the change in recognition among a specific audience.

The setting also benefits from the characteristics of the product—in this case, a pattern design. Unlike consumption goods, such as beers, the design is neither perishable nor depreciated by its consumption. Therefore, we could track the product’s users throughout its history. The panel data are constructed in a pattern-quarter format, and the model controls the quality of the pattern with pattern-fixed effects. Thus, the only independent variable is whether the focal quarter falls after the treatment, which takes the value of 1 if the designer has ever published in a top magazine before the quarter.
Because the distribution of projects is highly skewed and 67.3% of the pattern-quarter observations in the data have zero projects (Figure 3), we used quasi-maximum likelihood Poisson estimates with a pattern-level fixed effect (e.g., Hausman, Hall, & Griliches 1984). The model for the analysis is as follows:

\[
E(\text{DEMAND}_{ijt}|X_{ijt}) = \exp[\beta_0 + \beta_1 \text{ID}_SHOCK_{it} + f(Age_{it}) + g(Age_{jt}) + \delta_t + \gamma_{ij}]
\]

where \( \text{DEMAND}_{ijt} \) is the number of projects that pattern \( i \) by designer \( j \) attracts for quarter \( t \). \( f(Age_{it}) \) is a function of pattern age and is included as a series of indicator variables for the number of years since the pattern’s first release on Ravelry. \( g(Age_{jt}) \) is a series of indicator variables for designer age, measured as the number of years since the designer released her first pattern on Ravelry. To control the seasonal effect and/or Ravelry’s growth effect, a series of indicator variables for 29 quarters from 2007Q1 to 2014Q1 (\( \delta_t \)) are also included. Finally, \( \gamma_{ij} \) indicates the fixed effect for each pattern.

V. RESULTS

5.1. Typecasting as a Mainstream Producer

Figure 5 reports the difference in demand trajectories for the 10-quarter period following the designer’s mainstream identity shock. The zero point is the quarter when the designer first published her pattern in a mainstream magazine; negative quarters indicate the pre-publication period and positive quarters correspond to the post-publication period. The figure presents the negative effect of the identity shock, with clear contrasts in pre-publication and post-publication demand trends. To determine whether the control group of patterns matches the treated group of patterns with respect to the effect caused by the identity shock, the difference in effects before and after the shock is tested. In the figure, the identity shock is interacted with a set of indicator
variables corresponding to the number of quarters before/elapsed since the shock. In panel A, there is clearly no evidence of an effect in the periods up until the shock, which validates the identification strategy ex post (e.g., Azoulay et al. 2015). The difference graph dips into the negative only after publication, supporting the interpretation of a negative effect of publication. By contrast, in Panel B, the treated group exhibits a consistent downward sloping trend before and after publication, again supporting the appropriateness of the control group.

--- Figure 5 goes about here---

Section [A] of Table 3 further confirms that publication has a negative effect on the total demand in Ravelry, when quality is held constant. The first column (Model [1]) shows that the mainstream identity shock decreases the patterns’ probabilities of attracting more projects to the designer’s earlier patterns, compared with all the other patterns by unpublished designers. As shown in its low significance level, the effect is not large. Nonetheless, such a negative effect of publication might be regarded as surprising given the qualitative evidence showing that designers believe in the power of magazine publication in promoting the demand for their work. One possibility is that Ravelry population is more inclined to be young and “net-savvy,” so this pattern reflects the negative effect of mainstream publication in this community. To further investigate this question, we tested the effect for two different subgroups with competing identities: “traditional” and “avant-garde” knitters.

--- Table 3 goes about here---

The remaining columns of section [A] show the results for the subset of demand with group identifiers, the core of our DID analysis. First, Model [2] shows that the effect of the identity shock is consistently negative for the small subset of demand. In this subset, however,
we can see the differing reactions to identity shock according to the knitters’ self-defined identity. In Model [3a], we see that the negative effect is much stronger and significant among the avant-garde subgroup. On the other hand, in Model [3b], the traditional subgroup shows a slightly positive reaction to publications. The results imply that the negative effect is driven by the avant-garde knitters, who appear to punish a designer for her mainstream publication, even for earlier patterns for which no new information about their quality exists.

5.2. Typecasting as an Avant-garde Producer

We investigate the effect of a designer’s publication on knitty.com, an online magazine that appeals to young, “net-savvy” knitters. The analysis follows the same process as the main analysis in constructing treatment and control groups, but it uses a different treatment, i.e., the designer’s first publication in an avant-garde magazine. Section B of Table 3 shows that the results support our hypothesis that traditional knitters punish a designer’s publication (Model [3a]), and the general Ravelry population and avant-garde knitters nearly prize such publication (Model [1] and Model [3b]).

5.3. Robustness Check

We present two extensions to assess the integrity of the results. First, to investigate the possibility that the results depend on model specification, we tested an alternative specification of the linear probability model, given the skewness of the data, using the following analytic model.

\[
E(\text{DEMAND}_{ijt} > 0 | X_{ijt}) = \beta_0 + \beta_1 \text{ID\_SHOCK}_{it} + f(Age_{it}) + g(Age_{jt}) + \delta_t + \gamma_{ij}
\]

where DEMAND_{ijt} has the value of 1 if pattern i by designer j has any project that applied the pattern for the quarter t. f(Age_{it}) is a function of pattern age and is included as a
series of indicator variables for the number of years since the pattern’s first release on Ravelry. \( g(Age_{jt}) \) is a series of indicator variables for the designer’s age, which is measured as the number of years since the designer first released her pattern on Ravelry. \( \delta_t \) is a series of indicator variables for 29 quarters from 2007Q1 to 2014Q1, and \( \gamma_{ij} \) indicates the pattern’s age-fixed effect. A major advantage of using the linear probability model is the consistent sample size throughout the analyses, as no observation, even those with all zero values, is omitted. The estimates were mostly consistent with the Poisson estimates reported here, including those of interaction effects.

Second, to investigate the possibility that the results depend on how we define the treatment variable, we conducted the same analysis with two alternative measures: publication in a top-five mainstream print magazine (Knitter’s magazine, Creative Knitting, Knit Simple) or in a top-ten mainstream print magazine (Knit’n Style, Knitscene, Family Circle, Simply Knitting, Interweave Crochet). The results of the total demand remain similarly negative, while clear differences between the groups of competing identities were not observed in any alternative treatment in either the top five or the top ten magazines. The traditional group, which rewards publication in Vogue Knitting or Interweave Knits, no longer shows a positive reaction to publications when we broaden the scope of the treatment to include more minor mainstream magazines. Thus, publishing in the minor print magazines does not appear to be a positive identity shock for either group.

VI. CONCLUSIONS AND DISCUSSION

In this paper, we argue that there are distinctive characteristics of commitment based typecasting: asymmetric and retrospective inference. When a market exhibits an identity divide,
the inference for a producer's commitment generates asymmetric reactions toward the same information by audience identity. Moreover, based on this recognition, we argue that the audience tends to retrospectively reevaluate the producer's performances, thus influencing not only her future directions but also past work. When the producer's (true) identity is revealed to be contradictory with what the audience has assumed, the revealed identity becomes a new interpretive scheme, and the audience "retrospectively re-evaluates" her past performance to make sense of her entire career in accordance with the new interpretive scheme of commitment. Building on the two distinctive characteristics of commitment, our theory predicts that the demand for a producer's "previous" work declines when the producer gains recognition among audience of competing identity.

To empirically test the distinctive mechanism of commitment-based typecasting, we show that a producer's recognition in one category will result in decline in demand from the audience for a rival category, even when the audience remains certain about the capabilities of the producer. We use a natural experiment of a producer's "identity shock," a knit designer's public acquisition of a clear identity by publication in a prominent magazine. When a designer gains recognition among the audience of the traditional category, such recognition leads to lower demand among the audience of avant-garde category that holds an opposing identity to the traditional knitters. We stress two aspects of our result. First, the punishment is retrospective as the decrease in demand is observable even among the designer's patterns released before her recognition of public identity. Second, the results are symmetric as the traditional knitters also punish a designer's publication in an avant-garde magazine in the same way.

The empirical results enables us to distinguish two possible mechanisms by which a producer's identity is typecast and thereby affects demand. One possibility is that knitters care
about a producer’s identity as a signal to its capability to meet their particular quality standards. Indeed, the qualitative evidence generally suggests that knitters tend to justify their preferences in these terms. However, another possibility is that knitters care about the identity of a designer above and beyond the characteristics of the designer and the pattern. In fact, the categorization of a designer’s characteristics is not as distinctive as knitters of different identities insist. If the observable characteristics were clear, and avant-garde and mainstream designers truly produced highly different pattern designs, then there would be no question regarding their respective identities. Instead, there exists a level of uncertainty beyond objective product characteristics in defining the side to which a producer belongs. Moreover, this question of “sides” may matter greatly insofar as community members are committed to maintaining a clear boundary between their identity and others. From this perspective, uncertainty about the producer’s commitment makes it more difficult for the community to maintain a cohesive social movement. Audience members thus punish a producer by shifting their demand when it is endorsed by third parties that are affiliated with a competing identity because they experience this endorsement as an act of “betrayal” (e.g., Phillips et al. 2013).

The findings of the study also contribute to theories on social status. A dominant concept in social status theory is the “Matthew effect”—the idea that status orderings become self-perpetuating as high-status actors enjoy an increase not only in actual quality by being granted more resources but also in perceived quality by receiving favorable evaluations (e.g., Merton 1968; Azoulay et al. 2014). However, despite such increasing returns in social status, winner-take-all hierarchies are limited across a wide range of social contexts. Several sociological theories have attempted to explain why high-status actors cannot leverage their advantages to dominate entire markets, including lower-status niches. For example, Gould (2002) suggests that
the self-reinforcing status system breaks when actors prefer the reciprocation of their status-conferring actions. On the other hand, Podolny (2005) argues that high-status actors’ fears of status leakage limit the boundaries of their expansion to niche markets. For instance, mainstream magazines continue to publish the patterns of famous designers for fear of being viewed as on the “fringe.” Note that both mechanisms—reciprocality and status leakage—are based on the common assumption that a single quality standard defines status.

Tackling the assumption of single quality standard, this study suggests another mechanism that limits winner-takes-all hierarchies. Consistent with Zuckerman and Kim’s (2003) conjecture in the film market, the competing identities in cultural markets create conflicting status hierarchies; within each hierarchy, a distinct quality standard defines status. The diversion of each status hierarchy is encouraged by the inherent trade-off between two competing identities, as described by Stone (2009: p143), who argues that “to have an identity is to join with some and depart from others.” The identity shock studied here—publication in prominent magazines—enhances the designer’s status within the community of knitters who share the same identity statement and damages her status within the community of knitters who have a conflicting identity statement.

More generally, our findings illustrate the limits of convergence in social markets (Zuckerman 2012), such as the survival of many similar services in the social network service market, a market with strong network externalities. For example, the online messaging market reveals the presence of several different service providers (Lee, Song, & Yang, 2016), although strong network externalities should lead to a winner-takes-all equilibrium. Recent observations argue that such divergence relates to identity-based market segmentation, as shown in the demographic differences among these service providers’ users. Teenagers show strong
preferences for one over the other as a way of identifying their community, particularly for social
network services such as Twitter, Facebook, Instagram, and Snapchat. Therefore, identity-based
discrimination provides another mechanism to help explain why the winner cannot take all in
social markets, an interesting but underexplored topic in economic sociology.
REFERENCE


Figure 1: Impact of Recognition on the Inferred Commitment of a Producer
Figure 2: Structure of Ravelry.com

Note: Observable variables are bullet-pointed at each level of data. Designers create, upload, and sell patterns. Users download patterns and apply them to their own projects with their choice of yarns. Most designers have user accounts as well, and users can open their own designer accounts. The pattern page has the list of projects that applied the pattern, and the project page has the link to the original pattern to which the user applied the project.
Figure 3: Distribution of Project Applications per Pattern

Note: The right-most bar in this histogram corresponds to those patterns with more than 100 project applications. The maximum case is the pattern with 17,923 projects applications. The distribution of patterns over 100 projects is also highly skewed.
Note: We have two different groups of treated designers, each constructed by two kinds of identity shocks—traditional and avant-garde. For each identity shock, treated patterns include those that 1) are created by the treatment group (designers who have experienced the identity shock) and 2) are published before the designers’ first publication in major magazines. Patterns by non-published designers are set to control group patterns and are included in the following analyses, unless indicated as ‘treatment pattern only’ results.
Figure 5: Dynamics of the Traditional Publication Effect on Demand

A. Poisson Model, with controls

B. Poisson Model, without controls

Note: The solid line corresponds to coefficient estimates from conditional fixed effects quasi-maximum likelihood Poisson specifications in which demand (project application) is regressed onto quarter effects, pattern age indicator variables, designer age indicator variables, and interaction terms between treatment status and the number of quarters before/elapsed since the publication event. The 95% confidence interval (corresponding to robust standard errors, clustered around designers) around these estimates is plotted with dashed lines.
Table 1: Description of Knitters Group with Competing Identities

<table>
<thead>
<tr>
<th>Description of Knitters Group with Competing Identities</th>
<th>Traditional</th>
<th>Avant-Garde</th>
</tr>
</thead>
<tbody>
<tr>
<td>N distinct members</td>
<td>2,287</td>
<td>3,372</td>
</tr>
<tr>
<td>N members with projects</td>
<td>1,212</td>
<td>1,539</td>
</tr>
<tr>
<td>N projects by the group</td>
<td>19,399</td>
<td>14,363</td>
</tr>
</tbody>
</table>

- **<Over sixty> (N=131)**
  We are great fiber-lovers over 60 who embrace our age. We knit. We spin. We love fiber fests and sitting home on weekends if we choose.

- **<Knifty Fifties> (N=547)**
  It doesn’t matter if you just learned how to knit or have knit for a very long time, if you have reached that magical age of 50 (yesterday’s 40), then let’s get to know one another.

- **<grandma’s hand> (N=769)**
  We are Grandmothers who love being Grandmothers. We like to talk about our grandchildren as much as we love knitting, spinning, crocheting, etc. Grandmothers are Grandmothers no matter where we live so we welcome Grandmothers from all over the world.

- **<Fabulous and 50> (N=1212)**
  If you’re over 50--or plan to be one day--and are committed to the idea of ageing and knitting with grace and style, this group’s for you. We welcome posts about style, knitting, the concerns and delights of ageing, and things that everybody seems to be going through these days.

- **<i might like yarn, but i'm not your granny!> (N=720)**
  Are you a talented young knitter or crocheter bugged by society’s stance that you have to be elderly to enjoy crafts? Come here to rant, show off your amazing projects, and prove that it's not just for grandma anymore!

- **<The 20 Spot> (N=1467)**
  A group for knitters in their 20s to connect and share ideas about knitting and life.

- **<teens knit & crochet> (N=1385)**
  If you’re a teenage knitter or crochet who wants to connect with other teens who know what it is to be young with an 'old' hobby, here's the place to kick off your shoes and chat. Girls or boys, consider yourself officially invited!

Note: Descriptions are excerpts from the full introduction, and omitted parts include redundant descriptions and rules of the community. The list and the number of members are collected by 03/01/2015. Five members in both groups are treated as not included in any group.
Table 2: The Effect of Pattern Source on Project Applications

<table>
<thead>
<tr>
<th>Source</th>
<th>DV: Number of Projects Applied by All Identifiable Users by 2014Q1</th>
<th>DV: Number of Projects Applied by Traditional Users by 2014Q1</th>
<th>DV: Number of Projects Applied by Avant-garde Users by 2014Q1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vogue Knitting/Interweave Knits</td>
<td>0.744*** (0.201)</td>
<td>0.744*** (0.202)</td>
<td>1.018*** (0.192)</td>
</tr>
<tr>
<td>Knitty.com</td>
<td>1.104*** (0.167)</td>
<td>1.074*** (0.175)</td>
<td>1.008*** (0.172)</td>
</tr>
<tr>
<td>Second-tier Magazines</td>
<td>0.264 (0.203)</td>
<td>0.265 (0.206)</td>
<td>0.337* (0.142)</td>
</tr>
<tr>
<td>Miscellaneous Magazines</td>
<td>0.079 (0.106)</td>
<td>0.067 (0.108)</td>
<td>-0.086 (0.118)</td>
</tr>
<tr>
<td>Pamphlets, Local Yarn Stores, Calendars</td>
<td>0.100 (0.108)</td>
<td>0.073 (0.111)</td>
<td>0.010 (0.122)</td>
</tr>
<tr>
<td>Printed Material (Only Book Icon)</td>
<td>0.383** (0.136)</td>
<td>0.388** (0.139)</td>
<td>0.432** (0.132)</td>
</tr>
<tr>
<td>Private Source (blog, Ravelry store, etc.)</td>
<td>-0.094 (0.125)</td>
<td>-0.090 (0.132)</td>
<td>0.137 (0.119)</td>
</tr>
<tr>
<td>Designer Fixed Effect</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>N designer</td>
<td>12,306</td>
<td>7,569</td>
<td>7,569</td>
</tr>
<tr>
<td>N patterns</td>
<td>107,231</td>
<td>100,434</td>
<td>100,434</td>
</tr>
</tbody>
</table>

Note: All analyses are pattern-level cross-sectional Poisson estimations. Robust standard errors clustered by designers are in parentheses. Analysis [2] excludes those designers with single pattern or with zero project application across all of their patterns, so that the sample size matches to [3] with designer fixed effect. Indicator variables for 29 quarters when the pattern was created, free pattern, craft types, and 66 pattern categories are also included in the analysis. All source variables are mutually exclusive, and uncategorized source—the source name without any identifiable information from which we could infer the type of source—is the reference group. See Appendix for further information on the coding scheme of pattern sources. * p<0.05, **p<0.01, ***p<0.001
Table 3: Difference-in-differences Analysis of the Effect of an Identity Shock on Project Applications

<table>
<thead>
<tr>
<th></th>
<th>[1] Total Demand (Project Applications by All Users)</th>
<th>[2] Subset of Demand with Group Labels (3a+3b)</th>
<th>[3a] Demand by Avant-garde Knitters</th>
<th>[3b] Demand by Traditional Knitters</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ID_SHOCK</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Traditional)</td>
<td>-0.106 (0.067)</td>
<td>-0.099 (0.094)</td>
<td>-0.214** (0.104)</td>
<td>0.009 (0.102)</td>
</tr>
<tr>
<td>N designers</td>
<td>9,840</td>
<td>3,842</td>
<td>2,532</td>
<td>2,989</td>
</tr>
<tr>
<td>N patterns</td>
<td>64,425</td>
<td>11,312</td>
<td>5,677</td>
<td>7,945</td>
</tr>
<tr>
<td>N pattern-quarter observations</td>
<td>989,409</td>
<td>205,039</td>
<td>110,864</td>
<td>142,198</td>
</tr>
</tbody>
</table>

|                |                                                   |                                               |                                    |                                    |
| **ID_SHOCK**   |                                                   |                                               |                                    |                                    |
| (Avant-garde)  | 0.081 (0.103)                                     | -0.092 (0.126)                                | 0.111 (0.143)                      | -0.268* (0.143)                    |
| N designers    | 10,278                                            | 4,028                                         | 2,687                              | 3,165                              |
| N patterns     | 80,680                                            | 14,220                                        | 6,958                              | 10,161                             |
| N pattern-quarter observations | 1,223,317                                       | 256,500                                       | 135,058                            | 181,335                            |

Note: We have two different groups of treated designers, each constructed by two kinds of identity shocks—traditional and avant-garde. For section [A], ID_SHOCK (Traditional) takes the value of 1 when a designer experiences an identity shock by publishing in either Vogue Knitting or Interweave Knits for the first time in her career. For section [B], ID_SHOCK (avant-garde) takes the value of 1 when a designer publishes in Knitty.com for the first time in her career. The sample for the treatment group consists of published designer’s pre-publication patterns, and the control group consists of all patterns by unpublished designers. All models incorporate Poisson specification with a full suite of 29 quarter effects and 7 pattern age indicator variables and 7 designer age indicator variables. Robust standard errors clustered around designers are in parentheses. Patterns with all zero observations are automatically omitted. * p<0.05, **p<0.01, ***p<0.001
APPENDIX. Coding of Pattern Sources

If the name of a source includes specific words, such as “magazine” or “issue,” or a specific season, such as Spring 2015, we assumed that the source is a magazine. Among magazines, we construct a list of the 20 most prominent magazines from two sources: 1) magazines with popular issues, as defined by the top 200 individual issues on Ravelry and 2) those listed in the official guide of the “Designers” group on Ravelry from May 2014 to September 2014. Since the top two magazines—Vogue Knitting and Interweave Knits—are coded separately, we coded the remaining top 3–20 magazines as Second-Tier Magazines, other lesser-known magazines as Miscellaneous Magazines.

In addition to magazines, patterns can also be published in the local yarn stores’ pamphlets or calendars, which is coded as Pamphlets, Local Yarn Stores, and Calendars in our data. Besides the name of pattern sources, a book icon appears for the source of printed materials. Printed materials include books, magazines, and pamphlets/booklets but not e-books, web magazines, or webpages/blogs. The patterns published in print media that are not categorized as magazines or pamphlets are tagged as Printed Material.

Of course, not all patterns are linked to outside sources such as magazines or books. Many patterns’ designated sources are shown to be the designers’ personal webpages, blogs, Ravelry stores, and personal pages external to Ravelry (e.g., Etsy, Craftsy, Facebook, Google Docs). We categorize the patterns with source names that only correspond to one of the aforementioned personal sources as Private Source patterns. Therefore, the source variable is categorized into seven mutually exclusive categories: Vogue/Interweave, Second-Tier Magazines, Web Magazines, Miscellaneous Magazines, Pamphlets (Local Yarn Stores and Calendars), Printed Material, Private Source, and Uncategorized Source.