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Short communication

Household sector innovation in China: Impacts of income and motivation

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ABSTRACT

This research note reports upon the first survey of household sector innovation in China. Compared to previous survey studies we add two first-of-kind variables and related findings.

First, we include data on individual income, a resource-related antecedent of household sector innovation. We find that higher individual incomes are strongly associated with increased frequency of both household sector innovation and innovation diffusion. When we combine personal income effects with the positive impact of educational levels and technical training (both competence-related antecedents), it appears that increases in national development are associated with increases in household sector innovation - a very useful public policy finding.

Second, in this survey we included household sector innovations motivated by personal need and additional motivations related to learning, fun, helping others and selling/commercialization. This has a major impact on estimated household sector innovation frequencies - raising them by a factor of approximately 1.4. Reanalysis of data obtained in two earlier national surveys suggests that similar adjustment factors hold in those nations too. This finding shows that prior surveys have significantly underestimated household innovation. For many research purposes, such as national accounting, the total amount and value of household sector innovation is what is of interest, independent of motivations that may drive the activity.

1. Introduction and overview

A household sector innovation is defined as a functionally novel product, service or process developed by consumers at private cost (von Hippel, 2017: 1). In contrast to the business or government sectors, the household sector is the consuming population of the economy, in a word all of us, all consumers, “all resident households, with each household comprising one individual or a group of individuals” (OECD, 2013: 44). Household production entails the “production of goods and services by members of a household, for their own consumption, using their own capital and their own unpaid labor” (Ironmonger, 2000: 3). Household sector innovation, therefore, is a form of household production.

At the time of this writing, surveys of household sector innovation have been carried out in nine countries, showing that, in aggregate, tens of millions of individuals in these nations spend tens of billions of dollars annually developing and improving consumer products. In the study of household sector innovation in China we report upon here, we add two new important findings to the learnings from previous surveys and studies.

First, in the China survey we collect data on the income of household sector innovators. Previous studies have investigated competence-related indicators of consumers’ innovation ability, including education level and technical education and work experience (von Hippel, Ogawa and de Jong, 2011). Income, we suggest, adds an important resource-related dimension. Our analyses show that income is strongly related to levels of household sector innovation. Individuals at the highest income levels measured in China are 4 to 5 times more likely to innovate. In addition, we find that income is positively related to the likelihood of diffusion of household sector innovations. Specifically, at high incomes the odds of diffusion to peers more than double, while the odds of commercial diffusion are 15 times higher relative to those in the lowest income categories. When we combine the effect of income with previously-documented variables found significantly associated with household sector innovation (education level and technical work experience) a general picture emerges that the frequency and diffusion of household sector innovation is likely to increase along with global trends towards increased education and income.

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Second, we remove a key restriction included in prior surveys (de Jong, 2016). All prior surveys only reported on household sector innovations that respondents said were motivated by personal need. In the present survey, we also include innovations induced by additional motives: fun, learning, helping others, and selling/commercialization. When we do this, we find that the result is to raise the documented level of household sector innovation by a factor of 1.4. To increase researcher confidence in the generalizability of this correction factor developed by analysis of China survey data, we also go back and reanalyze data from two previous national surveys and find approximately the same factor present. This increase will clearly be important for many economic and policymaking analyses. For many purposes, analysts do not care *why* a household sector innovation was developed – only that it was.

In the sections that follow, we first review relevant literature (Section 2). Next, we describe our survey and analytical methods (Section 3). Then, we present our analyses and findings (Section 4), and conclude with a discussion (Section 5).

2. Literature review

2.1. Findings from prior household sector innovation surveys

At the time of this writing, nine national surveys have explored household sector innovation by individuals motivated to personally use what they develop. The surveys were carried out in the United Kingdom, the United States, Japan, Finland, Canada, South-Korea, Sweden, Russia and the United Arab Emirates (UAE) – see Table 1. All surveys utilized broad samples of individual end consumers. Estimates of population numbers were then generated by applying weighting procedures. Data were collected by means of a questionnaire administered by telephone interviewers in various countries (e.g., United Kingdom, Canada) and by means of internet surveys in other countries (e.g., United States, Japan, Finland). In one nation only (Russia) data was collected by face-to-face interviews. Questions asked in all studies included those asked in the initial survey of household sector innovation conducted in the UK. Later studies added some important additional questions such as those having to do with the motivation of household sector innovators. A basic survey script applied in the most recent studies can be found in de Jong (2016), and in von Hippel (2017).

Prior surveys demonstrate that household sector innovation is a major phenomenon. In aggregate across nations measured to date, tens of millions of consumers were found to spend billions of dollars per year developing and improving products. The percentage of populations innovating in the household sector differs quite significantly among nations surveyed. As can be seen in Table 1, the range was from 1.5% of the population in South Korea to 9.6% of the population in Russia.

To date, the significant variations in the percentage of consumers innovating among nations is not well understood. National surveys have only identified three major variables significantly associated with increased levels of household sector product innovation across all studies. These are higher levels of education, the presence of technical training or technical work experience, and male gender. By including the additional major variable of income in our data collection in China, we add a new dimension to the list of antecedents studied so far.

2.2. Income: Resources for household innovation

We hypothesize that income is positively related with individual household innovation. A range of studies about human behavior have shown that engagement in (any) volitional behavior partly depends on individual ability. For example, the theory of planned behavior offers perceived behavioral control as a key antecedent of individuals' decision to engage in volitional behaviors at work and in leisure (Ajzen, 1991). In the context of our study, theories of individual innovation have stressed ability-related antecedents as well. Examples include proactive motivation theory which distinguishes individuals' control beliefs in order to engage in proactive behaviors (Parker et al., 2010), and the compenential theory of creativity which includes creativy-related skills as a determinant of creative output (Amabile, 1983).

The survey studies of household sector innovation done so far did consider ability-related antecedents, but only related to individuals' personal competences to innovate. Thus, education level, technical training and technical work experience indicate personal innovation competence, or human capital relevant to household innovation. If a consumer encounters an unsatisfied personal need, seeks to learn, help others, make money, or simply enjoys the process of innovation, innovative behavior is more likely with better education, technical training and/or technical work experience.

We argue that income represents a different dimension of individual innovation ability. Controlling for education and technical training, income represents consumers' access to resources other than competence/human capital. In essence income reflects access to physical capital, that is, at higher income levels consumers are more likely to have access to technical resources (e.g., a workshop, development tools, software) and financial resources (to pay for out-of-pocket innovation expenses like materials, memberships, assistance). Moreover, high income indicates better opportunities to expand personal knowledge and abilities, e.g., by taking training. In this vein, studies of inventors (Meyer, 2005; Bell et al., 2017) have shown the importance of income for innovative behavior.

A second argument is that individuals with high incomes are usually more prosperous, and prosperity is known to make individuals pursue different life goals. Maslow's (1943) hierarchy of needs implies that at low prosperity individuals are concerned with subsistence, safety and belonging. In case such needs are met, which usually happens at higher prosperity levels, other needs become important: for instance esteem and self-actualization. Our reasoning is that at higher income levels consumers attach more value to life goals which can be accomplished by developing novel objects which do not yet exist.

Table 1
Proportion of population developing or improving consumer products for personal use.

Nation	UK	USA	Japan	Canada	Finland	S. Korea	Sweden	Russia	UAE
% of population	6.1[a]	5.2[b]	3.7[c]	5.6[d]	5.4[e]	1.5[f]	7.3[g]	9.6[h]	3.0[i]

Data sources:.
[a] von Hippel et al. (2012).
[b] von Hippel et al. (2011).
[c] von Hippel et al. (2011).
[d] de Jong (2013).
[e] de Jong et al. (2015).
[f] Kim (2015).
[g] Bengtsson (2016).
[h] Fursov et al. (2017).
[i] von Hippel et al. (2017).

A potential counterargument is that consumers at low incomes are deprived of resources to secure subsistence and safety. Such needs are likely to be quite acute. In support of this argument studies have provided existence proofs of the poor engaging in innovation (e.g., Praceus and Herstatt, 2017; Gupta, 2013; Goeldner et al., 2017). On the other hand, we notice that none of these studies involved broad consumer samples, and did not analyze innovations develop by more prosperous individuals. We expect that, being short on subsistence and safety, individuals with very low incomes are not necessarily triggered to develop innovative objects with functional novelty. Rather, at low incomes 'do it yourself' production (of already existing objects) may be more likely. Also, we observe that many, such as Prahalad (2004; 2012), have argued that the very poor want products different than those sought by those with more income – and that serving the "bottom of the pyramid" with commercial products uniquely suited to their needs was a market opportunity that producers had been neglecting. However, the argument made by these scholars was that *producers* should develop products suitable to the bottom of the pyramid – not that the innovations are developed *by* the poor.

We also anticipate that income will be positively related with the *diffusion* of household sector innovations. Again, income represent access to resources helpful for diffusion, and lowers the threshold to engage in diffusion behaviors (e.g., income enables individuals to spend money on diffusion, for example by sharing information about their innovation on the web) (Bell et al., 2012). Also, higher-order needs related to esteem and self-actualization, which are more prominent at higher incomes, make it more important to individuals to have their innovations become visible and adopted by others.

Altogether income adds a resource-based antecedent on top the competence-related antecedents studied so far. We expect that income will be positively related with household sector innovation and diffusion, also if education and technical work experience are controlled for.

2.3. Motives associated with household sector innovation

Until recently, national surveys of household sector innovation only considered innovations that consumers had developed for personal need. This was an unintended consequence – not noticed at the time - of terming non-producer innovators "users" (e.g., von Hippel, 2005). In the past few years, however, it has become evident that household sector innovators often are motivated by a range of incentives in addition to personal use (Raasch and von Hippel, 2013). These additional motives include: fun/enjoyment of innovation development work (Hienerth, 2006); learning and skill improvement (Bin, 2013; Hienerth, 2006; Lakhani and Wolf, 2005); helping others (Kogut and Metiu, 2001; Lakhani and von Hippel, 2003); and making money by selling the innovation (Meyer, 2005). In a survey of household sector innovators in Finland, a secondary data analysis (reported in von Hippel, 2017) of 408 household sector innovators incorporated these motivations. The analysis identified four major motivational clusters. "Users" (37% of the sample) expected their largest fraction of benefit to come from personal use of the innovation they had developed. "Participators" (43%) expected the largest fraction of their innovation-related benefits to come from self-rewards related to enjoyment plus learning from participating in the innovation process itself. "Helpers" (11%) were those whose strongest motivation asked about was to innovate in order to help others—altruism. "Producers" (9 percent of the sample) were most strongly motivated by the prospect of sales.

In this research note we will analyze the impact on household innovation frequencies of including this broader range of motives, rather than focusing on innovations motivated by personal need only. As was noted earlier, for many purposes, researchers and analysts do not care *why* a household sector innovation was developed – only that it was.

3. Methods

3.1. Sample and survey methods

We surveyed 5000 consumers in China aged 18 and over. Variation in income and education levels in China is substantial, making the country a good context for our research on the impact of these variables on levels of household sector innovation. In some geographical regions (e.g., Beijing, Shanghai) levels of income and education match those of the most prosperous regions across the globe. In other areas of China many have very low levels of income and education, similar to those encountered in much less developed parts of the world.

To identify the sampling frame for our survey, and also to carry out data collection, we collaborated with Dataway, a marketing research company based in Beijing. Because an exhaustive sampling frame with details of all Chinese citizens was not available, the initial sample was obtained with a random number generator covering both cell phones and landlines. To minimize the probability that we would get in touch with businesses, generated phone numbers were first filtered with a public database of all companies and public organizations. Also, data collection was done in the evenings to diminish the probability of contacting businesses, and the introduction to the survey explicitly mentioned our interest in consumer behavior, not business-related innovation. Our research approach insures that each citizen has an equal chance of being sampled (Malhotra and Birks, 2007). (Phone ownership in China is nowadays close to 100%. Cell phone ownership is 95%, and together with landlines coverage is close to complete (Pew Research Center, 2014).

Expert Dataway interviewers were selected and trained by our team, and only these few individuals were allowed to work on data collection for our study. Over a period of three months 37,403 Chinese citizens were sampled by these Dataway interviewers. For numerous reasons 11,120 citizens were impossible to contact (e.g., answering machine, no reply, unobtainable after five attempts). Another 21,283 refused to participate in the survey after being successfully contacted. At the conclusion of the data collection phase, responses were obtained from 5000 citizens, age 18 and older. The overall response rate was 19.0% of the individuals actually contacted.

With respect to demographic characteristics, 61% of the survey respondents were male. For education, 20% percent had a degree (bachelor, master or PhD), 33% had completed a secondary or college vocational school, and 47% had completed only high school or less.

In terms of age, 12% was 18–24 years, 26% was 25–34 years, 23% was 35–44 years, 18% was 45–54 years, 13% was 55–64 years, and 8% was 65+ years old.

As in previous survey studies of household sector innovation, we corrected for potential response bias by applying weights - to give the best possible population estimates. Compared to population characteristics taken from the China Population and Employment Statistical Yearbook (NBS, 2016) there was overrepresentation of males (population share 51%), highly educated (population shares: 9% has a bachelor/master/PhD degree, and 15% a secondary/college vocational degree), and younger citizens (population share of citizens <45 years is 52%). In contrast the poorest consumers were underrepresented. To obtain population estimates we computed weights for all respondents. Dataway provided us with a table which broke down the population of Chinese citizens aged 18 and over, across various combinations of gender, education and age classes. A similar table was obtained from our data, and weights were specified to be the ratio of the percentages in corresponding table entries.

3.2. Identification of household sector innovators

To identify innovations we applied the procedure summarized by de Jong (2016). We first identified if people had created or modified any items in the past three years. At the start of our survey we stated:

"*My next questions are about what you do in your free time. I would like to offer you some everyday items that you might have created or modified in your free time.*" In line with previous surveys respondents' recall was assisted by offering a list of nine specific cues: Had they created any (1) computer software; (2) household items; (3) vehicle-related; (4) tools or equipment; (5) sports, hobby or entertainment; (6) child or education-related; (7) health, care or medical; (8) fashion or clothing-related; or (9) any other items. Out of 5000 respondents, 803 reported developing or modifying at least one product in the past three years.

We then applied screening questions, to see if reported cases were household sector innovations. Specifically, to be included in the sample as a household sector innovation: (1) the product developed or modified must have been developed during leisure time; (2) must have been developed up to the level of a prototype actually used or applied in everyday life, and not simply be a not-yet-implemented idea; (3) must embody some functional novelty not available from items available on the market. We also asked respondents open-ended questions to describe what they had developed, and why. This enabled us to "double check" claims of functional novelty, enabled us to exclude esthetic or design-related innovations, and also enabled us to exclude homebuilt versions of products that could be purchased on the market. (We allowed coders to apply their own knowledge of what already exists in the market to, in clear cases only, exclude a development as non-innovative.) Each description was independently coded by two members of the research team. Cohen's Kappa was 0.91 indicating almost perfect agreement (Landis and Koch, 1977). In case of deviant codes, the descriptions were discussed to reach full agreement.

Out of 5000 respondents, 803 initially reported to have developed at least one product or product modification in the past three years. Our cross-check to identify and exclude job-related innovations reduced this number by 166, leaving us with 637 individuals who had created or modified at least one product in their free time during the past three years. Next, after our check on functional novelty we were left with 185 individuals who fulfilled all of our criteria for household sector innovators.

Previous surveys (e.g., von Hippel et al., 2012) applied an extra screening question, asking respondents if they had developed the innovation for personal need, to identify user innovators. In this survey we were interested in household sector innovators independent of motivation, and so did not screen out innovators with other motivations. Instead, we coded the motives driving respondents to develop the innovation (see later) to learn about the relative frequencies of household sector innovation independent of motive for development, and innovations developed specifically for personal use.

3.3. Variables collected via survey

Having established if a respondent was a household sector innovator, we then asked questions identical to those used previous surveys, in order to achieve comparability across all national surveys of household innovation. In the case of innovators who reported developing multiple innovations, we asked them to answer with respect to their most recently finished development only (see Table 2). In line with previous studies we asked for gender (dummy for males), education level (ordinal variable with six categories), being technically educated, and having work experience in a technical job.

To explore the relationship between innovation likelihood and personal income, we included an ordinal variable with nine categories ranging from an annual income of less than 10,000 Chinese Yuan, (about $1600 US at time of writing), to 300,000 Yuan, (about $47,000 US at time of writing) or more. (The latter is comparable to median incomes levels in the US and many European nations.)

We also added as a control variable whether the respondent lived in a rural area or village, a town, or a city/urban area. We did so because income may also indicate that individuals have better access to social capital for innovation. For example, in China currently, high-income people are more likely to live in densely populated areas and have access to supportive innovation infrastructure such as makerspaces. To ensure that income only reflects the theorized resource-related dimension and not social connectedness, we controlled for urbanity in our analysis.

We also asked questions regarding diffusion, including both commercial and peer-to-peer diffusion as alternative pathways (von Hippel, 2017), and respondents' time investment and if they had collaborated in order to innovate. Time investment and collaboration have been shown to influence diffusion (e.g., (Ogawa and Pongtanalert, 2013) and we wanted to control for these to better access the role of income. Finally, we asked for the innovator's most important motive for innovating (out of the five motives reported in Table 2). This question enabled us to analyze household sector innovation more broadly that previous surveys which, as noted earlier, had analyzed innovations motivated by personal use only.

4. Findings

In this section, we first present descriptive statistics with regard to the frequency of innovation, and the relationship of frequency to demographic variables including income. Next we analyze determinants of innovation and diffusion more deeply with regression models.

4.1. Frequency of innovation and demographic variables

Table 3 gives the percentages of innovators we observed in China across demographic variables. Notice that a weighting scheme has been applied to provide population estimates. As can be seen, and in line with previous studies, household sector innovators are more likely to be male, well-educated, technically trained, and have technical work experience. (We also measured age as a variable, but do not include it in Table 3 for space-saving reasons. No significant differences between age categories were found.)

In a finding novel to the China survey, we can clearly see a strong relationship between income and household sector innovation. In the top categories (200,000–300,000 Yuan and >300,000 Yuan annual income) the observed frequency of innovation is around seven times the frequency in the lowest categories (<10,000 Yuan and 10,000–30,000 Yuan). Table 3 also shows that citizens living in urban areas are more likely to innovate than those in rural areas. However, this finding vanishes when income is controlled for – respondents living in rural areas in China tended to have much less income than those living in cities (see Section 4.2).

4.2. Determinants of innovation

Next, we estimated probit regression models to explore the relationship between income and household innovation (and also diffusion) while controlling for competence-related and other independent variables. Table A1 (see appendix) offers descriptive statistics and correlations, showing that multicollinearity is not a concern. Regression output shown in Table 4.

Model I shows that innovation frequency is significantly related to educational level and (at marginal significance) with male gender and technical work experience. The model also confirms that income is significantly related to innovation, even when gender, age, technical education, technical job experience and education are controlled for. This is in line with our supposition that income reflects a resource-related dimension of innovation ability, and differs from the competence-related indicators studied previously.

To better interpret our findings Table 5 shows the predicted frequencies of innovation at various levels of income and education, the two most significant variables in our regression models. At the lowest level of education the predicted innovation frequency is only 0.7% when other variables are controlled for. For those with a master degree

Table 2
Variables.

Indicator	Description and values
(subject level - indicators available for all respondents)	
Household sector innovator	In the past three years, respondent created or significantly improved a product with functional novelty in his/her leisure time (0 = no, 1 = yes)
Gender	Respondent is (0) female or (1) male
Age	Age of the respondent (in years)
Urbanization	Respondent lives in a (1) rural area or village, (2) town, (3) city or urban area
Technical education	Respondent has a technical or science degree, or accreditation in a technical skilled trade (0 = no, 1 = yes)
Technical work experience	Respondent has work experience in a technical job (0 = no, 1 = yes)
Education	Respondent's best educational attainment is (1) none, (2) primary school, (3) high school or secondary vocational, (4) college vocational, (5) bachelor degree, (6) master degree
Income	Respondent's household income is (1) < 10,000 Yuan, (2) 10,001–30,000 Yuan, (3) 30,001–60,000 Yuan, (4) 60,001–80,000 Yuan, (5) 80,001–100,000 Yuan, (6) 100,001–150,000 Yuan, (7) 150,001–200,000 Yuan, (8) 200,001–300,000 Yuan, (9) 300,001 Yuan or more
(object level - indicators available for validated innovations)	
Time invested	Time invested to develop the innovation (number of person-days)
Collaboration	Number of people who provided help, assistance or advice to develop the innovation
Peer diffusion	Innovation has been adopted by peers (0 = no, 1 = yes)
Commercial diffusion	Innovation has been adopted by commercial firms and/or diffused in a venture (0 = no, 1 = yes)
Key motive	Respondent's motive to innovate was related to (multiple answers possible) (1) personal need, (2) to sell or make money, (3) to learn or develop skills, (4) to help other people, (5) fun/enjoyment

Table 3
Frequency of innovation across demographic variables.

Variable[3]	Observations	Frequency[1]
Total	5000	2.1%
Gender		
Female	1940	1.5%
Male	3060	2.7%
Urbanization		
rural/village	1452	1.4%
Town	1285	2.1%
city/urban	2263	2.9%
Technical education		
No	4339	1.8%
Yes	661	5.8%
Technical work experience		
No	3700	1.6%
Yes	1300	4.2%
Education[2]		
None	134	0.8%
primary school	486	1.0%
high school/secondary vocational	2072	1.4%
college vocational	1227	5.1%
bachelor degree	890	7.0%
master degree	97	3.3%
Income[2]		
less than 10,000 Yuan	779	1.0%
10,001–30,000 Yuan	949	1.0%
30,001–60,000 Yuan	748	2.5%
60,001–80,000 Yuan	452	3.2%
80,001–100,000 Yuan	465	3.4%
100,001–150,000 Yuan	381	7.3%
150,001–200,000 Yuan	191	1.7%
200,001–300,000 Yuan	133	6.3%
300,001 Yuan or more	233	7.5%

Notes:.
[1] To provide population estimates data are weighted on gender, age and education.
[2] For education and income the number of observations does not add up to 5000 due to missing values.
[3] For all variables reported in the table a χ^2-test showed significant differences at $p < .001$ (two-tailed significance).

(the best educational attainment) it is 7.2%. Likewise, for the lowest income category (< 10,000 Yuan) the predicted frequency is 1.4%. In the highest income category (300,001 or more Yuan) it is 5.9%.

In the bottom portion of Table 5, we report the predicted frequency of household innovation at a number of *combinations* of income and education. For example the predicted frequency for those without education and the lowest income is 0.4%, while for those with a master degree and the highest income it is 15.9%.

4.3. Determinants of diffusion

We next tested whether income also increases the likelihood of diffusion directly to peers, and diffusion via commercial pathways (i.e. transfer of the innovation to an existing producer, or commercialization via a startup venture). In model II of Table 4 we see that innovation collaboration and male gender are associated with peer-to-peer diffusion. In addition, income is positively related to diffusion to peers. We followed up estimating predicted frequencies of innovation at various income levels. Overall the predicted frequency of peer-to-peer diffusion is 33.2%. This implies that around one of three household sector innovations is adopted by peers. At the lowest income level (< 10,000 Yuan) the frequency was 19.8%, while at the highest level (300,001 or more Yuan) it was 53.0%.

In model III of Table 4 we see that technical education and male gender are related to commercial diffusion. In addition, income is (again) significant. Following up with predicted frequencies, at the lowest incomes (< 10,000 Yuan), only 0.6% of all innovations are predicted to diffuse commercially. At the highest level (300,001 or more Yuan) it was 23.2%.

These observations are in line with our presupposition that high income provides individuals with resources, which reasonably lowers their threshold to engage in diffusion. Specifically, income provides individuals with better access to diffusion resources (e.g., internet access, memberships) and probably also proxies the pursuit of higher-order life goals (e.g., self-actualization) which make diffusion more important to them personally.

4.4. Income-related robustness checks

We estimated various other regression models to check the robustness of our findings regarding income. These are available on request. First, our findings were maintained if we did not apply weights to our dataset.

Second, our descriptive statistics in Table 3 suggest that the relationship between income and innovation may be non-linear. We estimated probit regression models in which we included dummy variables for each income category, rather than income as an ordinal variable. For those with incomes of 150,001–200,000 Yuan household innovation frequency was not significantly higher than the baseline category of < 10,000 Yuan. This is probably be due to chance: drawing a random sample from any population does not lead to identical estimates, and occasionally, estimates based on a subsample may be lower

Table 4
Probit regression models of innovation and diffusion[1].

	I dy/dx	SE	II dy/dx	SE	III dy/dx	SE
Dependent variable	innovation		diffusion to peers		commercial diffusion	
Baseline value:	0.024		0.332		0.052	
Marginal effects[2]:						
male	0.0084^	(0.0050)	0.1917*	(0.0855)	0.0611*	(0.0307)
age	0.0001	(0.0001)	−0.0026	(0.0029)	−0.0006	(0.0014)
urban (vs rural)	0.0000	(0.0034)	−0.0591	(0.0587)	0.0086	(0.0136)
technical education	0.0029	(0.0088)	−0.0033	(0.0848)	0.1550**	(0.0469)
technical work experience	0.0145^	(0.0075)	0.0214	(0.0762)	−0.1092	(0.0907)
education level	0.0106**	(0.0030)	−0.0161	(0.0469)	−0.0141	(0.0149)
income	0.0043**	(0.0014)	0.0389*	(0.0159)	0.0241*	(0.0117)
time invested			0.0000	(0.0002)	0.0001	(0.0001)
collaboration			0.1942**	(0.0408)	0.0128	(0.0109)
Model fit:						
Pseudo R^2	0.084		0.226		0.314	
Wald-χ^2 (degrees of freedom)	114.5 (7)**		38.0 (9)**		45.9 (9)**	
Observations[3]	4117		159		159	

Notes:.
[1] Data were weighted to gender, age and education.
[2] Average marginal effects are shown. Robust standard errors in parentheses. Two-tailed significance.
** $p < .01$,
* $p < .05$, ^ $p < .10$.
[3] Number of observations for model estimations is effectively smaller than 5000 (model I) and 185 (models II and III) due to missing values on income, education level and age.

Table 5
Predicted innovation frequencies at levels of independent variables.

Independent variable	Predicted frequency
Education level:	
none	0.007
primary school	0.012
high school/secondary vocational	0.020
college vocational	0.032
bachelor degree	0.049
master degree	0.072
Income:	
less than 10,000 Yuan	0.014
10,001–30,000 Yuan	0.017
30,001–60,000 Yuan	0.020
60,001–80,000 Yuan	0.024
80,001–100,000 Yuan	0.029
100,001–150,000 Yuan	0.035
150,001–200,000 Yuan	0.042
200,001–300,000 Yuan	0.050
300,001 Yuan or more	0.059
Combinations of income and education:	
No education & < 10,000 Yuan	0.004
Primary education & 10,001–30,000 Yuan	0.008
Bachelor degree & 200,001–300,000 Yuan	0.099
Master degree & 300,001 or more Yuan	0.159

Notes: Data were weighted to gender, age and education. Average adjusted predictions are shown, based on the output of model I in Table 4. All predicted frequencies differ significantly from zero at $p < .01$.

(or higher) than one would usually expect. Apart from this issue, for models I and II our findings were confirmed: at higher innovation categories innovation and peer diffusion were significantly higher compared to the baseline category. (Model III did not converge, most likely as a result of entering too many independent variables in a model with few positive outcomes. Recall that only 5.2% of validated innovations diffused commercially.)

Third, we checked the robustness of models II and III by estimating sequential logit regression models (we thank an anonymous reviewer for this suggestion). Sequential logistic regression analysis estimates the effect of a set of independent variables on the odds of passing a specified number of transitions (Buis, 2011). We applied this model to predict the effect of male gender, age, urban (vs rural), technical work experience, technical education, education attainment, and income, on the 'transition' to household innovation (step 1) and subsequent diffusion to peers (step 2). When estimated simultaneously the significant variables related with innovation and peer diffusion were the same as those reported in Table 4. Next, we estimated a sequential logit model with commercial diffusion in the second step. Again, our findings were maintained, including that income is related with commercial diffusion.

Fourth, we recognized that income may be endogenous to household innovation and diffusion. Thus, we estimated an instrumental variables (IV) probit regression of household innovation. We used as instruments: region and mode of transport. Respondents in our dataset were from China's 31 regions (e.g., Shanghai, Beijing, Tianjing, Tibet, Inner-Mongolia). They had also indicated their main mode of transport: foot, bicycle, motorbike/electric cart, bus, subway/rail, car, taxi, and other (includes plane, boat, etc.). The IV probit model confirmed our findings with regard to the significance of technical work experience, education and income. However, the Wald test on the exogeneity of instrumented variables was marginally significant at $p < .10$, suggesting that our instruments were not sufficient. Therefore we explored the viability of our instruments more deeply by estimating a 2SLS regression model in which we (again) instrumented income by region and transport mode. On the positive side, the *F*-value of the instrumental variables was >10, while partial R^2 (of income on region and transport mode) was 0.1797, showing that the instruments were sufficiently related with income. However, Wooldridge's robust test was significant at $p < .01$, suggesting that the instruments are related with the structural error term. We therefore cannot exclude that endogeneity is present in our data. In our discussion section we call for longitudinal and multiple-source data to address these concerns in future research.

4.5. *Frequency of innovation as a function of innovator motivations*

Recall from Section 2.3 that, for all previous national surveys of household sector innovation except Finland and UAE, data collection was restricted to innovators motivated by personal need. Recall also that our present survey, conducted in China, had collected data on several innovation motives in addition to personal need. Our validated innovators reported the following (multiple answers possible) as important motivations driving their innovation development work:

Table 6
Frequency of household sector innovation[1].

	China (n = 5000)	Finland[2] (n = 2048)	UAE[3] (n = 2095)
Innovation frequency; personal need motive only	1.5%	5.4%	3.0%
Innovation frequency motivated by any of five motives	2.1%	8.4%	4.9%
Ratio personal need-only vs. all five innovation motivations	1.4	1.5	1.6

Notes:.
[1] In all three countries weighting schemes were applied to obtain populatin estimates;.
[2] Data source: De Jong et al. (2015);.
[3] Data source: von Hippel et al. (2017).

personal need (83%), sell or make money (5%), learn or develop skills (17%), helping others (23%), and fun/enjoyment (43%). In line with earlier work (von Hippel, 2017) personal need was most important, but nevertheless, to some consumer other motives were important as well.

As the basis for the second major finding in this study, we next analyzed the effects on innovation frequency from adding the aforementioned types of motivation to personal need. As can be seen in Table 6, the consequence of including innovations motivated by four additional sources of motivation is that the estimated percentage of household sector innovators documented in China increases by a factor of 1.4 (= 2.1/1.5). Personal use-motivated innovation in China is 1.5% of the population, or 16.5 million household sector individuals innovating in the previous three years. Personal use-motivated innovation *plus* innovations most importantly motivated by the additional motivation types listed above is 2.1% of the population, or 23.2 million individuals. This is, of course, a very substantial difference.

In an initial effort to determine whether this Chinese "correction factor" finding might be generally applicable in future studies of household sector innovation, we went back to the two earlier national household innovation surveys that had collected data on the same additional motivations, Finland and UAE. Reanalysis of data collected in those two studies show a very similar increase in innovations documented. That is, when one adds innovations motivated by these sources of motivation those motivated by user need, the percentage increase found is of significant size, and also very close to that found in China (Table 6).

Note that the levels of household sector innovation in China are clearly smaller than those measured in most other nations to date (c.f. Table 1). However, this may be largely a function of lower incomes and education levels in present-day China. In general across the world, citizens' education and income are improving over time. In practice these variables are related: better-educated individuals usually have higher incomes and vice versa. Assuming that economic growth in China continues in future decades, we expect that, along with increasing education and income, higher levels of household sector innovation will eventuate.

5. Discussion

As explained in our introduction, the first-of-type findings derived from this China survey study of household sector innovation are two: (1) the relationship between income levels and the likelihood that an individual householder will innovate and diffuse; and (2) a factor 1.4 increase in household sector innovation frequencies found when innovators' motives in addition to personal use value are allowed.

With respect to the impacts of income we found that, in China, when personal incomes are higher, household sector innovation frequencies and diffusion likelihoods are also higher. (This connection to income will likely be generally found: it has also been observed in studies of individuals' likelihood of inventing (Bell et al., 2017)). As we saw in Table 4, for Chinese citizens with annual incomes of between 200,000 and 300,000 Yuan, the household sector innovation rate was 6.3%. In 2017 the average incomes in the UK and Finland were in this range (25,500 Euros and 38,400 Euros respectively (www.tradingeconomics.com)) as were their household sector innovation rates of 6.1% and 5.6% respectively (von Hippel et al., 2012; de Jong et al., 2015). We therefore anticipate that the average percentage of household sector innovators in China will rise over time, as China continues its rapid development, and citizens' average incomes continue to rise.

With income our study adds a resource-related dimension of innovation ability, which differs empirically from competence-related ability measured by education level, technical training and technical work experience. Of course, in practice income and education are correlated, and collectively reflect consumers' general level of development. At the extremes of the development distribution, we found very strong differences between individuals at low income and no education, versus higher income and high education. It implies that in general, policies to advance a nation's level of development will go together with enhanced levels of household sector innovation and diffusion. Our findings also suggest that policy makers may want to put different priority to innovation by consumers at high versus low levels of development. At low levels of development consumers face more limitations in terms of innovation competences and physical resources, and would benefit more from policy interventions such as innovation tools and makerspaces. For China, today's education levels are still significantly lower compared to the US and Europe (OECD, 2017). However, major efforts are being made in China to increase educational levels over time (Jacob et al., 2018). Success at this will likely further improve future levels of household sector innovation and diffusion in the country.

With respect to motivations of household sector innovators, we suggest that it is reasonable that future national surveys also include, as we did here, innovations motivated by factors in addition to innovators' benefits from personal use. Consider that, for purposes of measuring the economic effects of household sector innovation, the specific motivations of innovators are a secondary issue. What counts is the number and value of innovations developed independent of motive. It is interesting to note that our reanalysis of data collected in household innovation surveys conducted in Finland and Emirates to include motives in addition to personal use value also produced adjustment factors in the range of 1.4. Therefore, researchers intending to use data from national surveys already done might reasonably consider using this ratio as an adjustment factor to findings as published to approximate household sector innovation frequencies.

5.1. Study limitations

It is important to note that surveys of household sector (HHS) innovation to date, including this one, have been conducted by academics who do not have "insider" access to exhaustive sampling frames (de Jong, 2016). It would clearly be preferable to use a sampling frame in which demographic data are known at the level of any potential respondent, so that potential response bias can be controlled for more thoroughly. The optimal scenario would be that a formal statistical office includes household innovation questions in an official consumer survey. In our study, we sampled respondents by means of a random telephone number generator. Given that the phone penetration rate for Chinese adults is well over 95% this is a viable method. Still, in company with all other national household innovation surveys conducted to date, it means that we could only control for response bias by weighting our data.

Second, although we do not believe that endogeneity has seriously affected our findings, the possibility certainly merits awareness. With regard to potential reverse causality, it is unlikely that household innovation and diffusion will have enhanced the incomes we observed.

Only 5% of the innovators had commercial motives, and also only 5% of the validated innovations had diffused commercially, so it is unlikely that innovation and diffusion ‘caused’ reported incomes. Also, with regard to common method bias our survey carefully followed Podsakoff et al. (2003) recommendations to minimize this potential problem, including upfront guarantees of anonymity, and carefully developed and tested questions. We avoided common answer formats and anchors, and our questions were mostly about ‘facts’ about very specific cues (e.g., ‘Computer software by programming original code. In the past three years, did you ever create or modify this in your free time?’). Our survey did not include the multiple-item measures used in psychological research which are more sensitive to common method bias. Finally, absolute values of the correlation coefficients between variables (see Table A1) were mostly minor ($r < 0.10$) and less than the correlations expected in the presence of common method bias when bivariate relationships are lacking (Podsakoff et al., 2003). Nevertheless, it would clearly be valuable for future research to investigate household innovation from a longitudinal perspective to deeply explore causal relationships. Alternatively, endogeneity threats can be minimized by collecting data from multiple sources.

5.2. Conclusion

Evidence for the importance of the phenomenon of household sector innovation is now strong. Ten national surveys, including this one, have all documented its importance. We are pleased we can add two novel findings to the growing research in this field via the study presented here. We very much look forward to further explorations and developments by fellow researchers.

Credit author statement

All authors contributed to the data collection, analysis, and writing involved in creating this paper. Jin Chen, first author, was responsible for getting permissions in China and making arrangements with a data collection firm to assist us.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix: Descriptive statistics and correlations

Table A1.

Table A1
Descriptive statistics and correlations.

		M	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
All respondents (n = 5000)														
(1)	HHS innovator	0.021	0.145											
(2)	Gender	0.52	0.50	0.042**										
(3)	Age	44.0	15.3	−0.001	−0.028									
(4)	Urbanization	1.98	0.88	0.046**	−0.032*	−0.047**								
(5)	Technical education	0.07	0.26	0.072**	0.105**	0.020	0.129**							
(6)	Technical work experience	0.21	0.41	0.074**	0.166**	−0.013	0.135**	0.343**						
(7)	Education	3.04	0.86	0.106**	−0.001	−0.045**	0.304**	0.286**	.169**					
(8)	Income	3.07	2.14	0.112**	0.159**	−0.186**	0.225**	0.173**	0.186**	0.313**				
Validated innovations (n = 185)														
(9)	Time invested	16.9	94.9	n.a.	0.099	0.036	0.049	0.153	0.095	0.031	−0.066			
(10)	Collaboration	0.49	2.52	n.a.	0.126	−0.052	−0.046	0.244*	0.146	−0.089	−0.098	0.039		
(11)	Peer diffusion	0.30	0.46	n.a.	0.342**	−0.200*	−0.186	0.119	0.129	−0.135	0.261**	0.003	0.250*	
(12)	Commercial diffusion	0.02	0.15	n.a.	0.137	−0.065	0.048	0.178	0.003	0.053	0.162	0.055	0.023	0.198*

Notes: Data were weighted to gender, age and education. M = mean, SD = standard deviation. Two-tailed significance.
** $p < .01$.
* $p < .05$.

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