Economics Bulletin

Volume 43, Issue 4

Influence of medical technology on entrepreneurial intention -evidence from China household survey

Chuanzhen Wu
College of Economics and Finance, Huaqiao University, Quanzhou, Fujian, 362021, China

Yunping Liu
College of Economics and Finance, Huaqiao University, Quanzhou, Fujian, 362021, China.

Abstract

This study empirically examines the relationship between medical technology and entrepreneurial intention. We use the panel data from the yearbooks of China Household Finance Survey (CHFS) and China Health Commission, and employ the fixed-effect regression with instrumental variables to reduce endogenous bias. This study reveals the bidirectional causality between medical technology and entrepreneurial intention. We emphasize that medical technology advancements can significantly stimulate entrepreneurial intentions, providing a new economic-boosting perspective for researchers. The results suggest to take economic benefits of the medical technology into account during policy making.

Citation: Chuanzhen Wu and Yunping Liu, (2023) "Influence of medical technology on entrepreneurial intention -evidence from China household survey", *Economics Bulletin*, Volume 43, Issue 4, pages 1842-1852
Contact: Chuanzhen Wu - wuchzhen@126.com, Yunping Liu - liu_yunp@126.com.
Submitted: June 15, 2022. **Published:** December 30, 2023.

1. Introduction

This study tries to find one of the driving forces of economic development, that is, the entrepreneurship intention, and discusses the impact of medical technology development on entrepreneurship. We assume positive feedback effect of medical technology on the economy. Medical treatment itself is a technology, and technical resources can be introduced to drive the economic development of the medical field. Lacking of correct medical guidance may turn a minor illness into a major one. Advanced medical technology can reduce the medical cost of minor illnesses leading to serious illnesses, reduce the pension burden of young and middle-aged people, activate the enthusiasm of young and middle-aged human capital for innovation and entrepreneurship, and further promote scientific and technological research and development and enterprise development.

The motivation is twofold. First, benefits for the policymaker. After Covid-19, local governments turn the focus from the fights against virus to the economy stimulation. One dilemma facing local governments is, under constrained budge, whether to meet high needs of investment in medical facilities, or high needs of investment in other economic sectors. The implicit presumption under this dilemma is that medical technology and economy are non-positive related, if the total budget is constrained.

However, the basic question, how medical technology affects economy, especially start-up business, has not been fully explored in previous studies. When economists study the economic value of technology, due to the high professional and technical nature of medical industry, medical-related studies are rather scarce. Most previous medical economic research focuses on medical costs. For example, Baicker and Chernew (2011) discussed the relationship between tax increases, medical stress, and GDP. Some others cover the impact of medical care on human capital (Culyer and Newhouse, 2000). Different from previous perspectives, this study shows that medical technology can improve the willingness to start a business, provide positive feedback for economic development, and then provide enlightenment for economic growth. This conclusion helps to optimize the allocation of budget resources.

Second, after Covid-19, public alertness of potential medical crisis has been fully awake, afraid of being unexpectedly stricken by accidents, idiopathic disease or contagious medical crises. The arising alertness urges us to explore how the medical alertness affect human behavior, especially entrepreneurial decision process in economic field.

We conduct regression on pooled data and panel data using instrumental variables. We use maternal mortality as a proxy variable for medical technology. The results show that the improvement of medical technology, that is, the decrease of maternal mortality rate, is significantly positively correlated with family entrepreneurship willingness. For every 1/100,000 reduction in maternal mortality rate, family entrepreneurship willingness increases by 14.45%.

2. Hypothesis

We assume that the medical technology can benefit the entrepreneurship through three channels. First, human capital. A few studies focus on the effect of human capital on entrepreneurship, the level of education in particular (Dimov and D. Shepherd, 2005). Different from the perspective of education, we emphasize that the medical technology can improve health level, stimulate the energy, inspiration, and motivation at work. Therefore, medical technology can affect human capital.

Second, financial capital. Medical technology can lower the possibility of "going to poverty due to illness", and decrease the average capital reserves for possible illness in each household. Hence, it increases capital reserves for families who are preparing to start a business. Capital reserves are essential for startups throughout the whole business process, even before the beginning of seeking opportunities.

Third, social capital. Better medical technology can change the maternal mortality rate, neonatal mortality rate, thus affecting household size. At the same time, it enables professional women recover sooner and healthier after giving birth, return to the workplace sooner, and corrects the discrimination against professional women. An increase in household size or the promotion of women's participation in occupational work can lead to greater social capital in the family. Studies have shown a positive link between social capital and entrepreneurship, with social capital helping to develop entrepreneurial motivation, identify business opportunities, and access entrepreneurial resources (Fuentes-Fuentes et al., 2015; Trigkas et al., 2020).

From the above theoretical analysis, the hypothesis can be put forward that "medical progress will positively promote entrepreneurial intention". Medical technology may become one of the points to start a positive cycle of social and economic development.

We observe the adoption of better medical technology, high medical cost and economic development are tightly intertwined. We assume that it is a causality loop. Reverse causality refers either to a direction of cause-and-effect contrary to a common assumption, or to a two-way causal relationship as a loop. We acknowledge the link from economic development to medical technology, that is wealthy persons can afford high medical expenses, fostering the adoption of better medical technology on the whole market. This process is natural and not help much on government budge decision. On the other hand, the other link from medical technology to economic development, which may help the government budge decision, has not been tested before.

To detect the effect under the situation of reverse causality, we use the lagged term *x*(*t*-1) to regress on *y*(*t*). To be specific, *y*(*t*) is entrepreneurial intention from the China Household Finance Survey (CHFS) in 2017 and 2019, *x*(*t*-1) is maternal mortality rate from the yearbook of China Health Commission (CHC) in 2016 and 2018.

3. Model

The basic model constructed is a linear probability model:

$$ENTRINT_{i,t} = \alpha_i + \delta_t + \beta_1 MMR_{k,t-1} + \gamma_1 EDU_{i,t} + \gamma_2 SN_{k,t} + \varepsilon_{i,t} \quad (1)$$

The dependent variable is entrepreneurial intention (*ENTRINT*). We measure it using national survey data. Corresponding questions in the China Household Finance Survey (CHFS) questionnaire are "whether members of the family have started a business" [B2000b] or "prepared to start a business in the next few years" [B2000d]. It is recorded as 1 if the answer is “yes” to either of the two questions. It is recorded as 0 if the answers are “no” for both questions. If both questions are not answered, it is recorded as a missing value.

To control the error of missing variables, we use instrumental variables in panel data for regression. The subscript i refers to the i-th household, k refers to the k-th province, and t refers to the t-th year respectively. We use the two-year datasets, 2017 and 2019, respectively. The coefficient α_i captures the characteristics of the i-th household that do not change with time which will be removed in panel data regression. δ_t represents the feature that varies with time, which will be incorporated into the constant term in panel data regression.

The influence of the explanatory variable, medical technology, has a time lag effect. We assume that it will spend at least one year to take effect. It is not easy to measure medical technology level. Medical technology includes hard and soft technology (Newhouse, 1992). Thus, advances in medical technology can include improvements in the speed and accuracy of diagnostic techniques, improved efficacy of drug treatments, and even advances in the analysis of pathology reports. Therefore, the measurement of medical technology adopts proxy variables. Number of medical equipment is used as proxy variable by Baker and Wheeler (1998). However, the number of medical devices only take hard technology into account and ignores soft technology. Dreger and Reimers (2005) adopted life expectancy and infant mortality.

At present, the commonly used indicators of medical output performance are life expectancy, maternal mortality rate, and infant mortality rate, popularized by World Health Organization. As to candidates of the proxy in the CHC yearbooks, data of perinatal mortality, expected longevity, maternal mortality rate (MMR) are reported. However, the first candidate, perinatal mortality, is strongly related to the antenatal care for mother. Furthermore, perinatal mortality effect is confounded. Medical technology help to lower the perinatal mortality. The increase rate of survivals may lower the return-to-work possibility of young and healthy mothers. The second candidate is “expected longevity”. The CHC yearbooks report expected longevity, instead of annually, normally every 5 years. It makes the data are not available. Besides of non-availability, it is not a suitable indicator. China now faces the problem of aging population, increasing life expectancy, but high costs of young labors. Among those candidates, the maternal mortality rate can measure the medical and health effects of young adults under physical conditions, which is most suitable for the characteristics of human capital suitable for entrepreneurship in this study. Therefore, the medical technology level was measured using the Maternal Mortality Rate (*MMR*) in the CHC yearbook.

The instrumental variable is the number of tier-3 hospitals (*HOS*). In China, hospitals are classified into three tiers according to Hospital Grading System: tier-1 (primary level), tier-2 (advanced level), and tier-3 (most advanced level). Maternal mortality ratio refers to the number of deaths per 100,000 pregnant women during the year. Maternal death refers to death from pregnancy to 42 days postpartum due to any cause related to pregnancy and pregnancy management, excluding accidental death. The number of tier-3 hospitals refers to the total number of tier-3 hospitals in the province that have been passed the evaluation until that year. We adopt the same year's data for the variables of the maternal mortality rate and the number of tier-3 hospitals.

Control variables include: (1) Household average educational level (*EDU*). Education is an important way for human capital accumulation. Educated people usually have stronger learning abilities to deal with complex problems, which increases the possibility of their entrepreneurship. Siqueira (2007) analyzed the 2000 census data in the United States and found that high school students and above show a high probability of starting a business independently, and the role of college education is more significant than high school education. Lim et al. (2016) confirmed that entrepreneurship is positively related to personal cognitive ability (Cognitive Dimension). At the same time, the establishment of mechanisms to improve cognitive ability at the national level can also help entrepreneurship. On the other hand, in China, more educated groups are more likely to obtain stable jobs, so they have a higher opportunity cost of starting a business, which reduces the possibility of its survival entrepreneurship. College students in China do not show high entrepreneurial rate like in other countries. Therefore, it is assumed that the influence of education level on entrepreneurship in China is non-linear. The average educational level per household is calculated by taking the average of the educational level of the individuals in each household. The corresponding question code in the questionnaire is [A2012]. (2) Social norm (*SN*). It is measured by the entrepreneurial ambience of the province. Social norms refer to the extent to individual's behavior is consistent with communities' thoughts. It is popular believed that entrepreneurship is related to norms (Li, 2021). Norms include social values, cultural context and beliefs. The entrepreneurial ambience of the province is measured by the ratio of the number of people who choose the answer "Starting a business is my pleasure or dream" to the total number of answers to this question in the province. The corresponding question is [B2001aa]: "What is the main reason for your family to engage in industry and commerce?".

4. Data

Variables such as entrepreneurial intention, social norm, household average educational level, come from China Household Finance Survey 2017 and 2019. The China Household Finance Survey are distributed in 29 provinces across the country, covering all mainland provinces, autonomous regions, and municipalities except Tibet, Xinjiang. The entrepreneurial ambience in the province refers to the ratio of the number of people whose are motivated as “being an entrepreneur is my ideal for the life” to the total number of people who answered the question "What is the main reason for your family to engage in industry and commerce?" in the province. The regions with the lowest entrepreneurial ambience were Inner Mongolia autonomous region in 2017 and Shanxi province in 2019. The highest region in the two years is Beijing. The average household education level refers to the average value of educational level under the same household ID number (hhid), 20-60 years old for the respondents in 2017 and 22-62 years old for the respondents in 2019. Household size is the total number of respondents under the same household ID number (hhid). The entrepreneurial intention is measured by "whether it has already started a business" or "planning to start a business in the next few years" in the data answered by the household.

The medical data, MMR and HOS, comes from the statistics of China Health Commission in 2016 and 2018, which collected the maternal mortality rate and the number of tier-3 hospitals in 29 provinces, autonomous regions, and municipalities. the maternal mortality rate was the lowest in Jiangsu Province in 2016, the lowest in Shanghai in 2018, and the highest in Qinghai Province in both years. The number of tier-3 hospitals in Guangdong Province is the most in both years, and the Ningxia Hui autonomous region is the least in both years. Two-year household data are matched by hhid. The samples with missing values in the variables are eliminated. Variables statistics are described in Table 1.

Table1. Descriptive Statistics

	Obs.	Mean	Median	Min	Max	Std. Dev.
ENTRINT	25729	0.2372	0	0	1	0.4254
EDU	25729	3.5758	3	1	9	1.47
SN	25729	0.1201	0.1195	0.0476	0.2593	0.0426
MMR	25729	12.6684	12.7	1.1	31.9	6.1925
HOS	25729	46.6413	42	4	115	24.1372

In Figure 1, the points in t=2019 is slightly downward and leftward than the points in t=2017, indicating lower mortality rate and lower entrepreneurial intention in t=2019 than in t=2017. The pooled data may be misleading by suggesting positive relationship between mortality rate and entrepreneurial intention, which is contrary to our hypothesis.

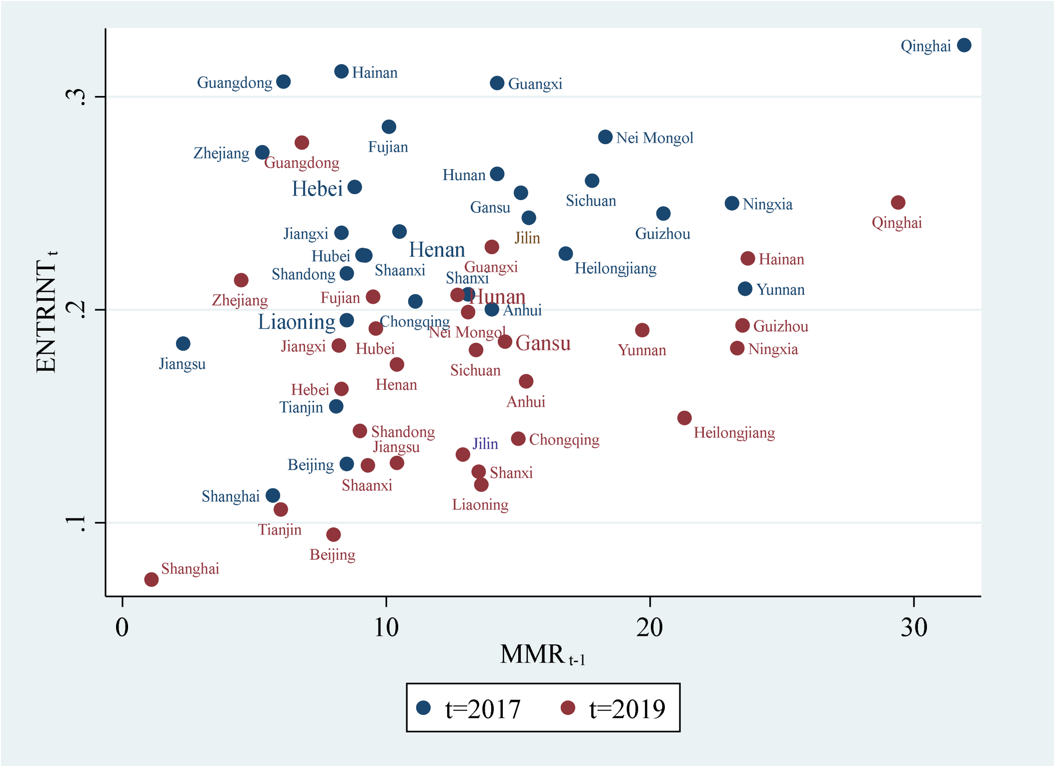

Figure 1. Maternal Mortality Rate (*MMR*) and Entrepreneurial Intention (*ENTRINT*) at Province Level

5. Results

The endogeneity of MMR should be considered, confirmed by the Hausman endogeneity test. In Table 2, columns 1 to 3 show the estimated results of linear probability model with instrument variable *HOS*, using pooled data. As to robustness, we compare the results with various models, including two-stage least squares regression (2SLS), limited information maximum likelihood (LIML), generalized method of moments (GMM). The coefficients of MMR in pooled data are very small and not significant, as presaged in Figure 1. Each province is heterogeneous. Using panel data is more appropriate.

In Table 2, columns 4 to 5 are results using panel data. The fixed effect model, compared to random effect model, is selected by the Hausman test. Column 4 reports the estimated results of fixed-effect regression models without instrument. Column 5 reports those coefficients with IV, i.e. numbers of tier-3 hospitals (HOS).

Table 2. Regression Results of Pooled Data and Panel Data

Variable	Pooled Data			Panel Data	
	2SLS (1)	LIML (2)	GMM (3)	Fixed-effect(4)	Fixed-effect with IV(5)
MMR	-0.0003 (0.0011)	-0.0003 (0.0011)	-0.0003 (0.0011)	-0.0020* (0.0010)	-0.1445*** (0.0185)
EDU	0.0165*** (0.0018)	0.0165*** (0.0018)	0.0165*** (0.0018)	0.0154* (0.0060)	0.0124 (0.0098)
SN	-0.5339*** (0.0726)	-0.5339*** (0.0726)	-0.5339*** (0.0726)	-0.0244 (0.0970)	-0.2758 (0.1608)
cons	0.2462*** (0.0224)	0.2462*** (0.0224)	0.2462*** (0.0224)	0.2099*** (0.0277)	2.0569*** (0.2424)
Obs	25729	25729	25729	25729	25729

Note：standard deviations are reported in parentheses. *: p<0.05. **: p<0.01. ***: p<0.001.

In Table 2, column 4 and column 5, the coefficients of medical technology represented by MMR on entrepreneurial intention are both significant and show the same sign. In the column 5, the coefficient of MMR in the fixed-effect model with IV shows the highest significance, which reaches -0.1445 at the 0.1% significant level. It implies that if the number of maternal deaths is reduced by 1 per 100,000 individuals on average, the average family's willingness to start a business will increase by 14.45%.

In panel data, the results in Table 2 change substantially when fixed effect IV is employed. The estimated coefficient with a fixed effect regression equal -0.002 (corresponding to an effect of +0.2%, also marginally significant) to -0.1445 (+14.45%) when IV regression is employed. Why?

One possible reason is the measurement error. In our paper, we do not have direct way to measure medical technology. The chosen variable Maternal Mortality Rate (MMR), reported in the yearbook of the Chinese Health Commission, may be measured with error if the data are misreported by local hospital or unreported due to giving birth at home in some rural areas. Or, in addition to medical technology, MMR may be affected by a few other variables which seems like random error under large sample assumption. If the change comes from measurement error, we may view IV method as an improvement in precision.

More problematic is whether the changes come from the bias, or in other words, loss in precision. The bias comes from poor instrument due to high corr(z,u) or weak instrument due to low corr(z,x).

As to the poor instrument due to high corr(z,u), it is reasonable to assume the correlation between MMR, i.e. x, and the number of tier-3 hospital, i.e. z, is negative, corr(z,x)<0. If corr(z,x)<0 and corr(z,u)<0, in common cases, we would assume corrr(x,u)>0. Then, OLS and IV estimator both have upward bias. If corr(z,x)<0 and corr(z,u)> 0, in common cases, we would assume corr(x,u)< 0. Then, OLS and IV estimator both have downward bias. Cited from Wooldridge (2019), "Unfortunately, we can never know for sure which estimator has the largest asymptotic bias". Luckily, both estimated coefficients of MMR, in OLS or IV, are negative as expected. We may say the main results are robust.

As to the weak instrument due to low corr(z,x), we make some test to confirm that weak instrument is not a big problem (Table 3)

Table 3. Relevant Test of Instrument Variable[1]

	test	statistics
underidentification	Kleibergen-Paap rk LM	Chi2=175.723(p =0.0000)
Weak Instrument	Kleibergen-Paap rk Wald	F= 173.749[2]
	Cragg-Donald Wald	F=96.861
Weak-instrument-robust inference	Stock-Wright	S=164.9356 (p=0.0000)
	Anderson-Rubin Wald	Chi2(1)= 167.7619 (p=0.0000)
		F= 167.7219 (p=0.0000)

Note: 1. These tests are performed using stata. Schaffer, M.E., 2010. xtivreg2: Stata module to perform extended IV/2SLS, GMM and AC/HAC, LIML and k-class regression for panel data models. http://ideas.repec.org/c/boc/bocode/s456501.html

2. Stock-Yogo weak ID test critical values at 10% maximal IV size is 16.38. Compared the critical values with the F-statistic of Kleibergen-Paap rk Wald test or Cragg-Donald Wald test, the selected instrument shows no sign of weak instrument.

6. Robustness Discussion

We make robust check in three ways, such as adding control variables, dropping control variables, dropping outliers.

First, we add GDP per capita as control variable in fixed-effect model with IV. Economic development may be correlated with number of hospitals. In robustness check step, we choose GDP per capita, the proxy of economic development, as control variable. To be specific, in the panel data, the variable named GDP_pc use the GDP per capita of the 2017 and 2019 yearbook of Chinese National Bureau of Statistics, as the same year as CHFS yearbook. To detect the t-1 effect, GDP_pc1 use the GDP per capita of the 2016 and 2018 yearbook of Chinese National Bureau of Statistics, as one year before CHFS yearbook. To detect the t-2 effect, GDP_pc2 use the GDP per capita of the 2015 and 2017 yearbook of Chinese National Bureau of Statistics, as two years before CHFS yearbook.

Table 4. Adding GDP as controls

	(1) GDP_T	(2) GDP_T-1	(3) GDP_T-2
MMR	-0.183^{***} -0.0386	-0.111^{***} -0.0186	-0.0729^{***} -0.0106
EDU	0.0116 -0.0114	0.0127 -0.0084	0.0132 -0.0072
SN	-0.328 -0.228	-0.0627 -0.183	0.345^{*} -0.143
GDP_pc	0.0000 0.0000		
GDP_pc1		-0.0000^{**} 0.0000	
GDP_pc2			-0.0000^{***} 0.0000
Obs	25174	25174	25174

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As shown in Table 4, adding GDP per capita and the lagged term by each province will change the size of MMR coefficients. All the coefficients of MMR in three models, the core variable we are interested in, are negative and significant at $p < 0.001$ level in the above three models. We also make instrument variable test, as shown in Table 5. We may say the main result of MMR are robust.

Table 5. Relevant Test of Instrument Variable[1]

Model	Category	test	statistics
GDP_T	underidentification	Kleibergen-Paap rk LM	Chi2=33.94(p =0.0000)
	Weak Instrument	Kleibergen-Paap rk Wald	F= 34.882
		Cragg-Donald Wald	F=22.12
	Weak-instrument-robust inference	Stock-Wright LM	S=60.65 (p=0.0000)
		Anderson-Rubin Wald	Chi2(1)= 61.80 (p=0.0000)
			F= 61.78 (p=0.0000)
GDP_T-1	underidentification	Kleibergen-Paap rk LM	Chi2=135.13(p=0.0000)
	Weak Instrument	Kleibergen-Paap rk Wald	F= 267.337[2]
		Cragg-Donald Wald	F= 134.946
	Weak-instrument-robust inference	Stock-Wright	S=53.82 (p=0.0000)
		Anderson-Rubin Wald	Chi2(1)=53.96 (p=0.0000)
			F= 53.94 (p=0.0000)
GDP_T-2	underidentification	Kleibergen-Paap rk LM	Chi2=300.059(p=0.0000)
	Weak Instrument	Kleibergen-Paap rk Wald	F= 173.749[2]
		Cragg-Donald Wald	F=96.861
	Weak-instrument-robust inference	Stock-Wright	S= 59.08 (p=0.0000)
		Anderson-Rubin Wald	Chi2(1)= 59.05 (p=0.0000)
			F= 59.03 (p=0.0000)

Note: 1. These tests are performed using Stata. Schaffer, M.E., 2010. xtivreg2: Stata module to perform extended IV/2SLS, GMM and AC/HAC, LIML and k-class regression for panel data models. http://ideas.repec.org/c/boc/bocode/s456501.html

2. Stock-Yogo weak ID test critical values at 10% maximal IV size is 16.38. Compared the critical values with the F-statistic of Kleibergen-Paap rk Wald test or Cragg-Donald Wald test, the selected instrument shows no sign of weak instrument.

Second, we drop some control variables to test whether the coefficient is robust.

Table 6. Robustness check by changing control variables

	(1) test1	(2) test2	(3) test3	(4) test4	(5) test5	(6) test6	(7) test7	(8) test8
MMR	-0.183*** -0.0386	-0.183*** -0.0386	-0.176*** -0.0367	-0.145*** -0.0155	-0.142*** -0.0148	-0.145*** -0.0156	-0.176*** -0.0368	-0.142*** -0.0148
EDU	0.0116 -0.0114		0.0115 -0.011	0.0124 -0.0097	0.0122 -0.0095			
SN	-0.328 -0.228	-0.326 -0.229		-0.276 -0.193		-0.274 -0.193		
GDP_pc	0.0000 -0.0000	0.0000 -0.0000	0.0000 -0.0000				0.0000 -0.0000	
Obs	25174	25174	25174	25174	25174	25174	25174	25174

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$

Third, we drop outliers, such as Qinghai (Model outlier1, ourtlier2) that stands on the upper right corner and Shanghai (Model outlier3, ourtlier4) that stands on the lower left corner in Figure 1. The coefficients of MMR are still negative.

Table 7. Outlier Test

	(1) outlier1	(2) outlier2	(3) outlier3	(4) outlier4
MMR	-0.145*** (0.0156)	-0.238*** (0.0599)	-0.132*** (0.0137)	-0.153*** (0.0291)
EDU	0.0144 (0.0099)	0.0125 (0.0143)	0.0130 (0.0093)	0.0124 (0.0102)
SN	-0.337 (0.195)	-0.502 (0.293)	0.888*** (0.198)	1.036*** (0.293)
GDP_pc		0.0000116* (0.00000572)		0.00000288 (0.00000267)
Obs	24384	24384	24284	24284

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7. Conclusion

This paper reveals the bidirectional causality between medical technology advancements and entrepreneurial intention. It is believed that economic development fosters the adoption of better medical technology, that is wealthy persons can afford high medical expenses, fostering the adoption of better medical technology on the whole market. The contribution of this study is to highlight that the direction of causality is also from medical technology to entrepreneurial intention, using panel data with instrument variables to control endogeneity. The positive link from medical technology to entrepreneurial intention has been long neglected in previous literature. From a theoretical perspective, understanding the link between medical technology and entrepreneurial intention will shed new light on future entrepreneurship research by providing a new economic-boosting perspective. Furthering our understanding the value of some specific medical technologies and learning how best to facilitate them calls for future research.

One possible implication is from a public policy perspective. The study suggests that the policy makers who are limited in budgets, ought to be reminded that some of the economic promotion activities, such as adding the government budgets on fix-assets investment at the cost of cutting the budgets of medical technology investment, may be missing the long-term economic benefits. For the policy makers who emphasize the long-term benefits, this study suggests that the facilitation and support of medical technology investment may provide an effective support for emerging businesses, along with current solutions of business incubators that offer subsidized rent or marketing assistance.

Another possible implication of this study is for organizations who fund medical research. Cleary et al. (2018) examine the contribution of NIH and find private pharmaceutical companies have limited incentives "to make investments toward basic research that would negatively impact near-term earnings, offer uncertain competitive advantage, and may not generate profitable products for decades." This study justifies the needs for public financing on medical fields, by adding the long-term benefits in economic evaluation of medical technology.

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