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Education–Technology Synergy and Urban Economic Growth: An Empirical Study Based on Prefecture-Level Panel Data in China

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Abstract. China transitions to innovation-driven growth and makes education and technology investment a core component of the policy agenda, yet the economic effect of their combination has not been thoroughly studied. Using the panel data of prefecture-level cities from 1998 to 2020, this research constructs a mean-centered interaction term in the two-way fixed effects framework to examine whether these two investments can strengthen each other when promoting urban growth. The baseline results indicate that investing in a single technology presents an evident negative effect, and the main influence of education is not statistically significant; nevertheless, the interaction term has been consistently positive and rather significant. After multiple tests this finding still remains highly reliable including setting first-order differences and excluding municipalities directly under the central government. Regional analysis further shows that the synergy effect is obviously stronger in the eastern region than in the central and western regions and this difference has been verified through the Wald test. These findings not only challenge the concept that education and the technology can operate independently but also offer support for the policy logic of "cultivating talents first and then seeking innovation".

Keywords: Education investment, Technology investment, Synergy effect, Economic growth, Two-way fixed effect

1. Introduction

China's ambitions for innovation-led growth have pushed education and technology investment to the center of urban economic policy. An extensive empirical literature reveals that education spending promotes long-run growth by building human capital, while technology investment can directly lift productivity and upgrade industrial structures [1-3]. Yet increasing both types of investment simultaneously does not guarantee a larger growth return. The growth effect of education is slow to materialize, with short-run estimates often weak or even negative, reflecting the long gestation period of human capital [4, 5]. Technology spending, meanwhile, often fails to convert into growth when the local workforce cannot absorb or apply the new technologies—a scenario labeled "ineffective matching" [6].

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When these findings are considered together, it is rather confusing. The more important issue is whether these two inputs function as complementary goods, each enhancing the effect of the other. Recently, the research has tracked the chain of "human capital's innovation's growth", has clarified the role of education in the long-term deepening of human capital, and has also revealed the spatial spillover effect between regions, among which the distinction between effective and ineffective matching provides a direct analytical framework for the synergetic effect [5-8].

Despite these advancements there still exist two interrelated deficiencies the first one is of a conceptual nature. Recently, theoretical research has made it clear that human capital and R & D investment are in a relationship of strategic complementarity—without the other, any one input is ineffective, and it is the composition of human capital, not its total level, that determines the economy's ability to absorb and apply new technologies [9, 10]. However, these insights are rarely transformed into a universal experiential framework; most research still models education and technology expenditures as independent drivers of growth without introducing interaction terms that can formally test complementary logics. Another weakness does lie in the spatial and methodological aspects indeed. A large number of existing evidences mostly rely on the aggregated data at the provincial level which can cover up a great deal of intra - provincial heterogeneity. The researchers have pointed out that the central and western regions may benefit from the progress of green technology because of the comparative advantages in human capital, however, their analysis does not directly construct a model of the interaction between education and technology input [11]. Moreover the endogeneity problem that comes from the two - way relationship between local investment decisions and economic growth is rarely dealt with strictly at the local level. Therefore the structure and regional aspects of education - technology synergy have not been explored thoroughly at the prefecture level either.

This research directly tackles these limitations. It constructs a panel of Chinese prefecture-level cities ranging from 1998 to 2020 and then estimates a two-way fixed effects model that includes the mean-centered interaction term between per capita education and technology expenditures. Within the two-stage least squares framework of endogenous regressors, the setting of instrumental variables with their own lagged values is carried out and the research results are verified through multiple robust tests. This article has three contributions. First, it converts the argument of strategic complementarity into an empirical assertion that can be tested at the local level [9, 10]. Through directly estimating the interaction coefficient, this research is employed to examine whether the combined growth effect of education and the technology surpasses the sum of their respective independent contributions - a hypothesis that the existing literature has for the most part not examined. Second, this article divides the synergy into regional components. Based on the evidence of different human capital returns among China's macro regions, the interaction between education - technology terms and regional dummy variables will be carried out, and then the joint Wald test will be used to evaluate the system differences [11]. This method is not simply making a general statement that synergy is important but rather seeking out the regions where synergy is most prominent — this finding has a direct influence on the spatial allocation of financial resources. The comparison between the two - way fixed effects and the first - difference estimation further differentiates the long - term structural synergy and the short - term fluctuations. Thirdly, the evidence presented in this paper has reoriented the mainstream policy statements. It turns out that the traditional practice of only separately emphasizing increasing education or science and technology expenditure is wrong; instead, the logic of "cultivating talents first and then pursuing innovation" has received strong empirical support, and there are significant differences in the intensity of this synergy in regions with different human capital endowments.

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2. Theoretical mechanisms and hypotheses

The growth effects of education and technology investments are by no means independent of each other, and they interact through human capital accumulation as well as the absorption and creation of new technologies. Simply increasing either of them alone is not likely to maintain growth—their synergistic effects are precisely the key that transforms potential into productive forces. Education investment, which acts as a main means to form human capital, can expand the human capital reserve of a region and is also the prerequisite for technology absorption and dissemination [8]. However, its returns have a rather significant time lag. Educational expenditures will suppress growth in the short term yet become clearly positive over a longer time span, showing a pattern of "short - term costs, long - term returns" [5]. Therefore, in a concurrent model, the main impact of educational investment may seem insignificant or even negative. Not because education is useless, but because its payback period is far longer than the current period. The growth is propelled by science and technology investment that supports research and development and stimulates technological progress [3]. However, its effectiveness depends crucially on the local human capital foundation indeed. When the direction of human capital and technological progress coincides, they will promote each other; if there is insufficient human capital, the investment in technology may lead to improper resource allocation instead of bringing about the improvement of productivity as stated in [6]. In a benchmark model not considering this conditional aspect, a negative coefficient will appear when only focusing on technological investment, which reflects the mismatch effect occurring when there is a lack of human capital support. These two observations point to a core assertion: an additional growth effect is generated by the interaction between the two inputs, and neither of them alone can generate it. When there is an abundant amount of human capital, workers are more prone to absorb, apply, and re - innovate on the basis of new technologies, which boosts the marginal output of technological expenditure and then triggers a virtuous education - technology cycle, as Wang and Li recorded when tracking the complete "human capital→innovation→growth" transmission chain [7]. Therefore, the interaction term has turned into a way for directly testing whether the combined effect surpasses the sum of independent contributions. The degree of such synergistic effects is not likely to be the same in different regions. In the more developed eastern regions that are full of high-quality human capital, the technology investment is more apt to form an effective matching with the human capital, thereby generating stronger synergetic effects. In the central and western regions, by contrast, human capital endowments are relatively smaller and absorptive capacity is weaker, so the same level of technology spending may yield a muted—or even absent—synergistic effect [1, 2]. Based on the above analysis, this paper proposes two testable hypotheses:

Hypothesis 1. The marginal effect of technology investment on economic growth depends on the regional level of human capital. The interaction term between education and technology investment is significantly positive—that is, education and technology exhibit a synergistic growth effect.

Hypothesis 2. The education–technology synergy displays significant regional heterogeneity. The synergy is stronger in the eastern region than in the central and western regions, whose economic growth benefits less from the effective matching between education and technology.

3. Data, variables, and model specification

The dataset is assembled from the China Urban Statistical Yearbook and supplementary provincial and municipal yearbooks, covering 6,501 city-year observations for Chinese prefecture-level cities from 1998 to 2020. After removing observations with missing values or invalid logarithms, 3,714

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valid observations remain—a loss of about 43 percent, typical for such panel data. Given the short-panel structure (large N, small T), and following existing practice , a separate unit root test is not performed; stationarity is verified through the first-difference model in the robustness checks [7]. The dependent variable is log real per capita GRP (ln_pgdp). Core independent variables include per capita education expenditure (edu_pc) and per capita technology investment (tech_pc), defined as education and S&T fiscal expenditure divided by year-end population [1, 3, 4]. Their mean-centered interaction term (edu_tech) captures the synergy [6]. Control variables include fixed asset investment intensity (invest), urban employment ratio (urban), government intervention (gov), trade openness (ln_export), and road passenger and freight volumes (ln_infra1, ln_infra2). Complete variable definitions, along with their measurement and sources, are detailed in Table 1, which is placed at the end of this section for reference. A complete summary of all variable definitions and descriptive statistics is presented in Table 1.

Table 1. Variable definitions and descriptions

Types of variables	Variable name	Variable symbol	Formula mode
Dependent variable	economic growth	ln_pgdp	The natural logarithm of the per capita actual regional GDP is taken.
Core independent variable	Per capita education expenditure	edu_pc	Educational Expenditure(ten thousand yuan)/Population(ten thousand people)
Core independent variable	Per capita technology investment	tech_pc	Expenditure on science and technology(ten thousand yuan)/population(ten thousand people)
Core independent variable	Interaction term(centralization)	edu_tech	$(\mathrm{edu_pc}-\overline{\mathrm{edu_pc}})\times(\mathrm{tech_pc}-\overline{\mathrm{tech_pc}})$
control variable	Fixed asset investment intensity	invest	(Fixed asset investment/10,000)/Regional GDP
control variable	Urban employment ratio	urban	(The total number of employees in urban units+the total number of employees in urban private and individual enterprises)/population

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Table 1. (continued)

control variable	Degree of government intervention	gov	(General Public Budget Expenditure of the Region/10,000)/Regional Gross Domestic Product)
control variable	the level of opening	ln_export	The actual amount of foreign capital utilized in that year(in thousands of US dollars)is transformed into natural logarithms.
control variable	Transportation(passenger)transportation)	ln_infra1	transformed into natural logarithm.
control variable	Transportation(for freight)	Ln_infra2	transformed into natural logarithms

The model is a two-way fixed effects specification, as can be seen in formula (1)

$$lnpgdpit = \alpha + \beta_1 edu\_pcit + \beta_2 tech\_pcit + \beta_3 edu\_techit + \gamma Xit + \mu i + \lambda t + \varepsilon it \quad (1)$$

Where X includes the control variables, μ_i and λ_t are city and year fixed effects, and ε_it is the error term. All variables are mean-centered before interaction, with VIFs below 10. F-tests and Hausman test support the two-way fixed effects model, and clustered robust standard errors at the city level are used throughout. To address endogeneity, 2SLS employs first-period lags of edu_pc and tech_pc as instruments , with the interaction term treated as exogenous [2, 7]. Lagged education terms were excluded from the baseline due to high collinearity (VIF > 30). To test Hypothesis 2, the model interacts edu_pc, tech_pc, and edu_tech with regional dummies for the central and western regions and uses joint Wald tests. The sample displays considerable cross-city variation. ln_pgdp has a mean of 10.09 (SD = 0.81). Education spending averages 841.91 yuan (SD = 824.50), and technology spending averages 97.28 yuan (SD = 309.77), with the latter exhibiting greater relative dispersion. The interaction term's large mean (197,817.40) arises from multiplying mean-zero variables and does not affect coefficient estimation.

4. Empirical results

Before estimating the baseline model, specification tests are conducted. The F-tests for individual fixed effects (F = 23.759, p < 0.001) and time fixed effects (F = 577.04, p < 0.001) both reject the null, indicating that both city-specific heterogeneity and common time shocks must be controlled. The Hausman test further negates the random effects specification and on the contrary supports the fixed effects with a chi - square value of 13,410 and a p value less than 0.001.These results consistently support the two - way fixed - effect model.

Table 2 shows the baseline two-way fixed effects estimations, the 2SLS results as well as the variance inflation factors, with the internal coefficient of determination being 0. And all VIF values are kept below 10, with the situation of serious multicollinearity being excluded. Three key findings appear. Firstly,the main influence of education investment (edu_pc)is not statistically significant

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(with a coefficient of 2.At 98e - 05, with p being 0.362, this is in line with the time lag situation recorded in the previous research [4, 5]. In the second point, the technical investment (tech_pc) shows a rather remarkable negative coefficient (where the coefficient is equal to -2.00e - 04, with p less than 0.001, which conforms to that "ineffective matching" mechanism. In this mechanism, if the human capital is insufficient, what is generated by the technological expenditure is resource misallocation instead of the increase of productivity [6]. Thirdly the interaction term (edu_tech) of educational technology is significantly positive with a coefficient of 1.33e - 08 and the p - value is less than 0. Assumption 1 is confirmed with the 001 citation format being included. Positive interactions show that the combined contribution of education and technology is more than the sum of their respective individual impacts, which accords with the logic of strategic complementarity [9, 10]. Among the control variables, government intervention has a significant negative effect, while trade openness and freight infrastructure have a significant positive effect. The point estimates and 95% confidence intervals of all explanatory variables as presented in Figure 1 rather directly supply graphical support for the core hypothesis.

Education and technology expenditures are potentially endogenous, as faster-growing cities can afford larger fiscal outlays. To address this, first-period lags of edu_pc and tech_pc are employed as instruments in an exactly identified 2SLS model. The first-stage F-statistics are 5,198.9 for edu_pc and 2,076.9 for tech_pc, substantially exceeding the Stock-Yogo threshold of 10, confirming that weak instruments are not a concern. The 2SLS results in Table 2 show that after controlling for endogeneity, edu_pc becomes significantly positive (coefficient = 3.56e-04, $p < 0.001$), suggesting that its baseline insignificance was partly attributable to reverse causality bias. The coefficient on tech_pc remains significantly negative (coefficient = −6.64e-04, $p < 0.05$), reinforcing the mismatch interpretation. The interaction term becomes statistically insignificant ($p = 0.906$). This change is not contradictory: the interaction term is constructed from two endogenous variables, and its own endogeneity is more complex than that of the main effects [6].

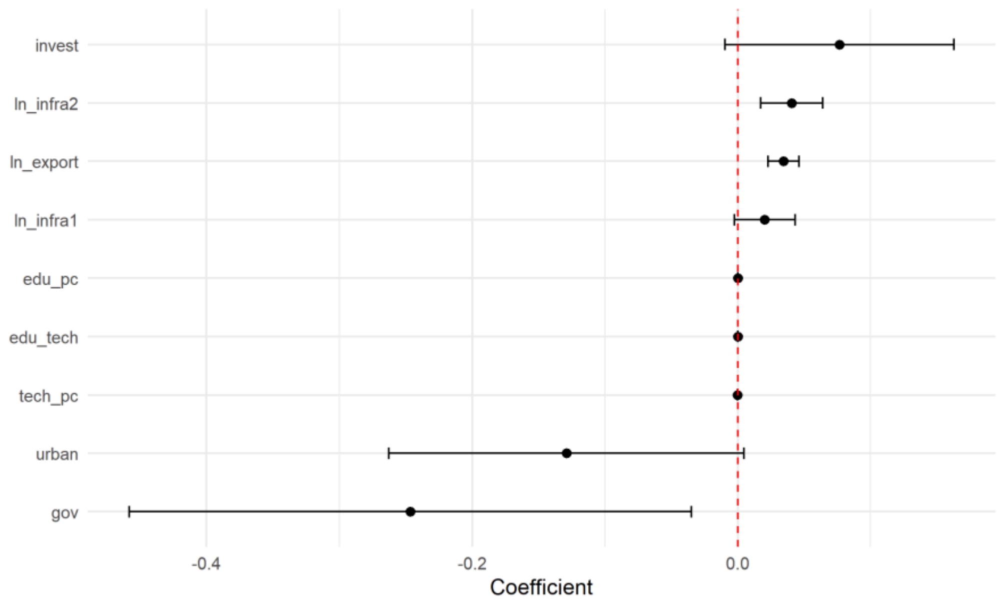

Figure 1. Coefficient and confidence interval of core variable

The detailed coefficient estimates corresponding to Figure 1 are reported in Table 2, which also includes the 2SLS results discussed below.

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Table 2. Results of baseline regression and endogeneity handling

Variable	Coef_fe	SE_fe	p_fe	Coef_iv	SE_iv	P_iv	Vif
edu_pc	0	0	0.362	4e-04	1e-04	0	7.3026
tech_pc	-2.00E-04	1e-04	7e-04	-7.00E-04	3e-04	0.0456	8.9852
edu_tech	0	0	7e-04	0	0	0.9055	4.9545
invest	0.0766	0.0439	0.0814	0.0946	0.051	0.0639	1.8257
urban	-0.129	0.0681	0.0583	0.8119	0.1157	0	3.556
gov	-0.2464	0.108	0.0225	-2.2148	0.5622	1e-04	1.5583
ln_export	0.0346	0.006	0	0.1181	0.0117	0	2.0996
ln_infra1	0.0203	0.0117	0.082	-0.1072	0.01	0	1.7608
ln_infra2	0.0406	0.0119	6e-04	0.0905	0.0099	0	2.1723

Within R^2=0.1168,The coefficients in the FE model are exact values. Due to the precision setting, they are displayed as 0. Within R^2 is the within-group R-squared of the two-way fixed effects model.

Four robustness checks are performed to assess the reliability of the baseline findings. First, when the log of per capita GDP is replaced by the GDP growth rate, all core variables become insignificant.

Theoretically, this is predictable for the reason that the growth impacts of education and technology work over a long time period and will not be well manifested by annual fluctuations [5]. Second after excluding the four directly governed municipalities namely Beijing Tianjin Shanghai and Chongqing tech_pc is still clearly negative and edu_tech is clearly positive which implies that the core outcomes are not brought about by those outlier instances. Thirdly, this paper confine the sample from 2003 to 2020 so as to exclude the possible structural changes that might take place around the turn of the century. After having done this, the symbols and significances of the two things, namely tech_pc and edu_tech, still do not have much change indeed. For the fourth point, the setting of the first-order difference (FD) eradicates the time-invariant city fixed effects and captures the short-term changes within the cities. The results of FD present the situation where the interaction term has a sign reversal (with a coefficient of -8.7.6e - 09 with p less than 0.001 forms a distinct contrast with the two - way fixed effects estimation. This difference supports such an interpretation that the collaboration between education and the technology is essentially a long-term structural phenomenon. The FE model captures the structural differences between cities, under which there exists a very strong positive synergy effect. And the FD model separates the short-term annual fluctuations, in which the resource crowding-out effect of educational expenditure is dominant [5]. The results are summed up in Table 3.

Table 3. Results of robustness tests

Term	Coef_gdp growth	Coef _without DC	Coef _2003-2020	Coef_fd model	Se_gdp growth	Se _without DC	Se _2003-2020	Se_fd model
edu_pc	6e-04	0	0	1e-04***	0.001	0	0	0
tech_pc	0.0021	-2e-04***	-2e-04***	0	0.0026	1e-04	1e-04	0
edu_tech	0	0***	0***	0***	0	0	0	0

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"0" in the table indicates that the absolute value of the coefficient is less than 1e-08. Significance levels are denoted as *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To test hypothesis 2, the interaction term between the baseline model and the core explanatory variable and the regional dummy variable is added. The interaction term of education - technology is significantly negative for the central region with a coefficient of -1. The western part (with a coefficient equal to -1.72e - 07 and p less than 0. Those regions, which indicates that the synergy effects in these regions are significantly weaker than those in the eastern part, and the differences in these regions are shown in Figure 2. In the educational dimension, the coefficients of the central and western regions are indeed all higher than the benchmark of the eastern region. However, in the interaction dimension, the point estimates of the central and western regions are all clustered near the zero line, which is different from the significantly positive interaction situation in the eastern region.

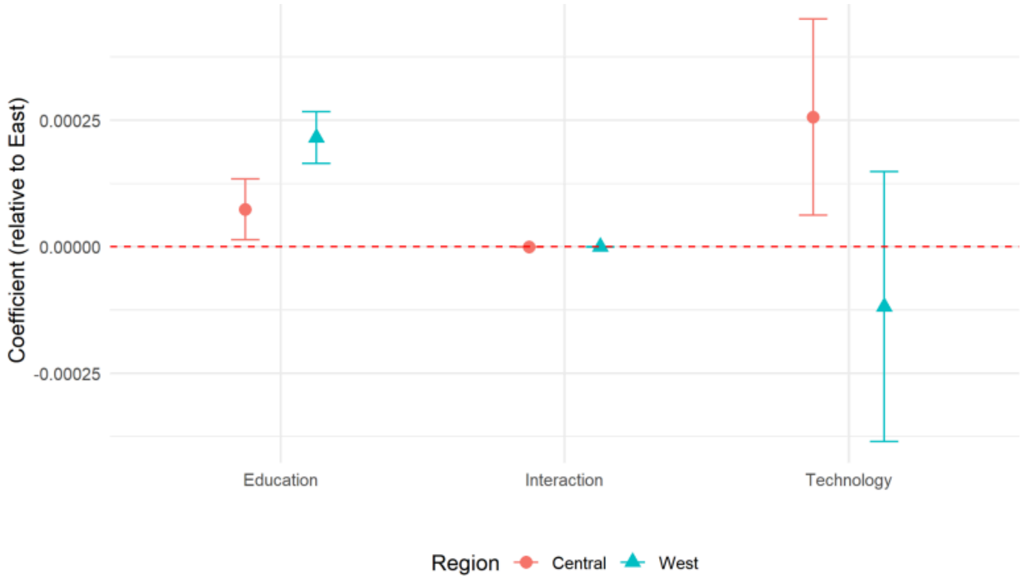

Figure 2. Comparison chart of regional adjustment effects

The joint Wald tests reported in Table 4 strongly reject the null hypothesis of no systematic differences for central China ($\chi^2 = 25.06$, $p < 0.001$), western China ($\chi^2 = 74.66$, $p < 0.001$), and all regions combined ($\chi^2 = 85.86$, $p < 0.001$). The coefficients in the FE model are exact values. Due to the precision setting, they are displayed as 0. These results confirm Hypothesis 2: the education–technology synergy exhibits significant regional heterogeneity, with the eastern region benefiting far more than the central and western regions, consistent with the view that a mature innovation ecosystem and concentrated human capital are prerequisites for the synergy to materialize [1, 2].

Table 4. Interaction model of all sample regions

Term	Estimate	Std.error	Statistic	P.value
edu_pc_Central	1e-04	0	2.4266	0.0153
edu_pc_West	2e-04	0	8.2692	0
tech_pc_Central	3e-04	1e-04	2.5915	0.0096
tech_pc_West	-1.00E-04	1e-04	-0.8695	0.3847
edu_tech_Central	0	0	-2.1121	0.0348

Table 4. (continued)

edu_tech_West	0	0	-2.293	0.0219

5. Conclusion

Using the Chinese prefecture-level city panel data set from 1998 to 2020 this study through the two-way fixed effects model and the instrumental variable method to explore the impact of education-technology synergy on urban economic growth has obtained four main findings. First of all the respective independent growth effects of education and technology investment are relatively limited. In the basic model education has no statistically significant effect whereas technology alone shows a significant negative impact. Secondly, there is an obvious synergy effect: after removing the urban area and shortening the time window, the interaction term remains positive and stable all the time. Thirdly, this synergy effect is fundamentally long-term and structural, becoming insignificant in the instrumental variable regression and changing sign in the first-difference model. Fourthly the synergy effect presents obvious regional differences and the joint Wald test verifies that the synergy effect in the eastern region is far stronger than that in the central and western regions. Generally speaking the core finding is that the collaborative interaction between education and technology rather than their respective separate expansions is the key driving force for urban economic growth. Then there are three policy - related implications. First of all, the government should adhere to the logic of "cultivating talents first and then pursuing innovation". Secondly, various regional strategies are indeed necessary. The eastern region should strengthen the integration of education and technology, and the central and western regions should focus on expanding education to lay the foundation of human capital. Thirdly, the return cycle of education investment is relatively long, which then requires carrying out performance evaluation over a relatively long period of time.

However, there are still some limitations indeed. Approximately 43% of the sample losses that may have an impact on representativeness and the satellite nighttime light data that can be used for cross - validation. The endogeneity treatment of interactive items remains incomplete, and using the system generalized method of moments or policy shocks as instrumental variables is a potential alternative approach. The spatial correlation between cities has not been considered, and spatial econometric models can be employed to study the spillover effects among cities. Finally, the mechanism test depends on theoretical inferences, and future work can directly test intermediate channels like human capital accumulation.

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