The Roles of Preventive and Curative Health Care in Economic Development

Master's thesis

Istanbul Technical University, Department of Economics
Anna Pirogova | pirogova23@itu.edu.tr

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Health = core component of **human capital** and **productivity**

Global **rise** in health expenditures → pressure on public budgets

Policymakers often assume that all health expenditure is equally growth-enhancing, but:

💉 Curative care → treats existing illness
🛡️ Preventive care → reduces risk of illness

→ **Different mechanisms, different economic roles.**

⚖️ OECD countries: **aging populations & fiscal constraints** → optimizing health investment is critical for sustainability and long-term growth.

Research Gap

Existing studies rarely focus on **both health care spending** components

Lack of evidence on **separate effects** of curative vs. preventive care

Nonlinearities (e.g., thresholds) often ignored

💰 Effects may differ by **income level or institutional context**

🎓 Few models test **interactions with education spending**

🔄 **Endogeneity** rarely addressed systematically

Research Questions:

❓ What are the separate effects of curative and preventive health spending on the real GDP per capita?

❓ Do these effects exhibit nonlinear (threshold-based) behavior?

❓ How do these effects vary across countries with different income levels?

❓ Does the impact of curative health spending depend on the level of education investment?

Hypotheses:

💡 H1: Curative health spending is expected to have a stronger and more direct impact on the real GDP per capita than preventive spending.

💡 H2: The relationship between health spending and real GDP per capita is nonlinear, involving threshold effects.

💡 H3: The positive effect of health spending on real GDP per capita is stronger in higher-income countries.

💡 H4: Greater education investment strengthens the positive effects of curative health spending.

Health as Human Capital
Becker (1964), Mushkin (1962), Grossman (1972)

Health-Led Growth Hypothesis
Better health → ↑ productivity, ↓ absenteeism
GDP per capita as proxy for development

Prevention vs. Cure Debate
Prevention = harder to measure, long-term effects
Only ~20% of interventions are cost-saving
Effectiveness is context-dependent

Optimal Allocation (Wang, 2016–2021)
Nonlinear returns to both spending types
Underinvestment → missed gains
Overinvestment → marginal returns, inefficiencies

Health spending → positive economic effect

•OECD: Beylik (2022), Atilgan (2024)

•Developing countries: Baldacci (2004), Piabuo & Tieguhong (2017)

Prevention: nonlinear and threshold effects

•Wang (2021, 2024): optimal prevention share ≈ 1.2%; underinvestment harms productivity

•Hu & Wang (2024): income threshold affects spending impact

Our study vs. Literature

•Uses **balanced OECD panel (1998–2021)**

•Employs **FE and DML** (not GMM)

•Tests **nonlinearity and interactions with education, income decomposition**

Data Description

📊 **Sample**

29 OECD countries:
Australia, Austria, Belgium, Canada, Czechia, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Italy, Japan, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Slovakia, South Korea, Spain, Sweden, Switzerland, UK and the USA

Period: 1998–2021
→ Balanced panel
→ Total observations: 24*29=648

📁 **Data Sources:**

OECD Health Statistics
World Bank, UN, UNESCO

📌 **Key Variables:**

Dependent Variable
Log of real GDP per capita (2010 USD)

Main Independent Variables:
Curative health expenditure (% of GDP)
Preventive health expenditure (% of GDP)

Control Variables:
Demographics: Life expectancy, elderly population share, total population
Economic: Education spending (% of GDP), trade (% of GDP), savings (% of GDP), short-term interest rate

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Data Description – Summary Statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
Real GDP per capita (2010 US $)	**38789.60**	**21778.28**	**5627.55**	**127117.10**
Trade (% of GDP)	90.94	56.64	18.13	393.14
Population size (millions)	41.44	62.02	0.27	332.05
Population ages 65+ (% of total)	16.20	3.78	4.78	29.79
Life expectancy (years)	79.49	2.80	70.13	84.56
Public spending on education (% of GDP)	5.18	1.19	2.89	8.61
Savings (% of GDP)	6.32	6.18	-15.71	27.92
Short term interest rate (%)	2.83	3.51	-0.80	27.10
Total health care (% of GDP)	**8.81**	**2.22**	**3.60**	**18.60**
Curative health care (% of GDP)	**4.98**	**1.46**	**1.72**	**11.90**
Preventive health care (% of GDP)	**0.26**	**0.15**	**0.00**	**1.27**

Table 3.1 : Summary Statistics.

Cross-Country Variation:

GDP per capita: $9,247 (Mexico) — $95,359 (Luxembourg)

Life expectancy: 73.8 years (Mexico) — 82.8 years (Japan).

The share of the 65+ population: <5% — ~30%

Curative health expenditure: 2.96% (Mexico) — 10.2% (USA).

Preventive spending: 0.12% (Greece) — 0.59% (Canada).

Trends in Average Health Spending (OECD, 1998–2021)

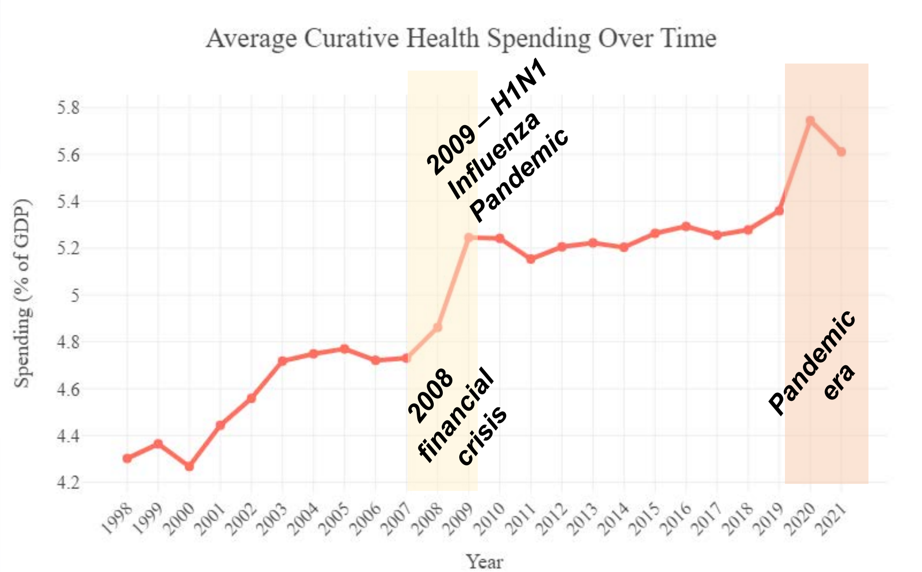

Figure 3.1 : Average Curative Health Expenditure Over Time.

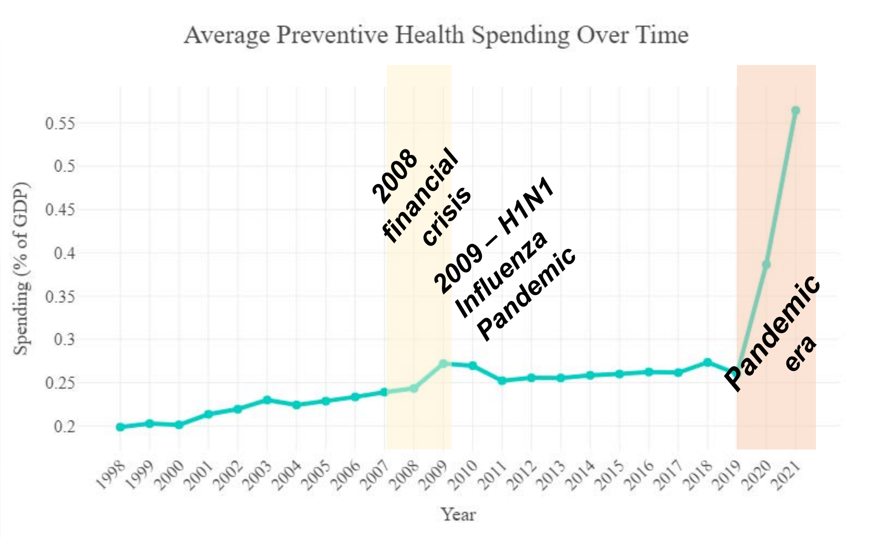

Figure 3.2 : Average Preventive Health Expenditure Over Time.

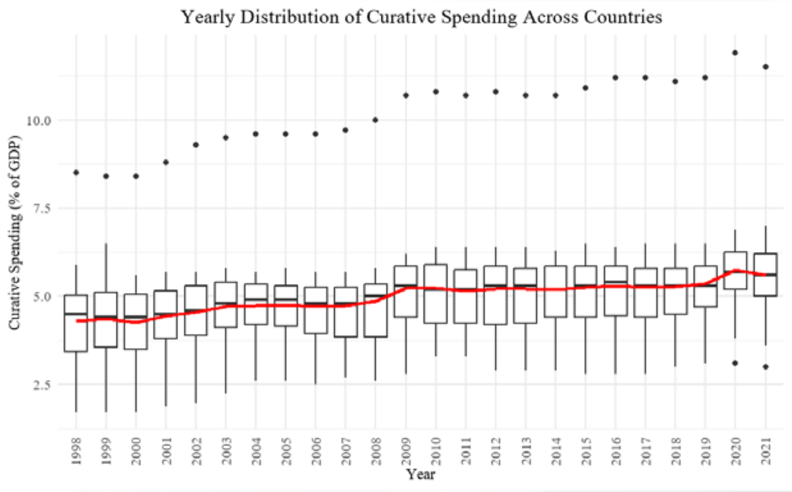

Figure 3.3 : Box-plot Distribution of Curative Expenditure Over Time.

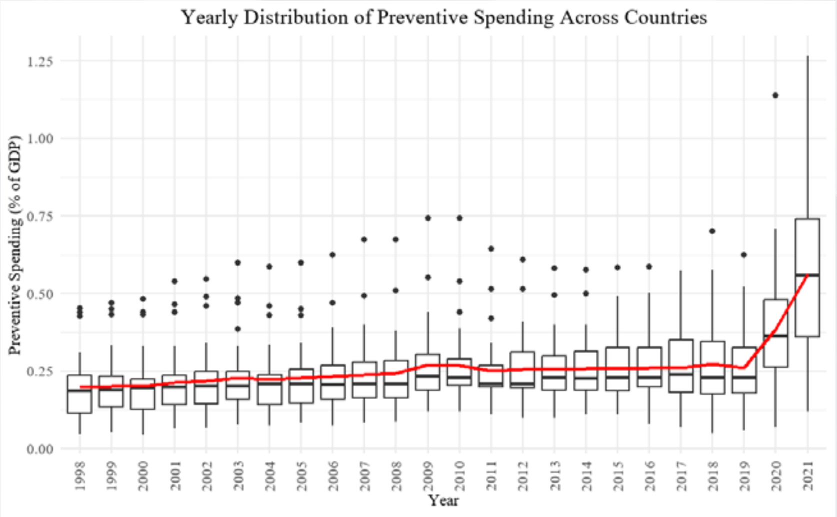

Figure 3.4 : Box-plot Distribution of Preventive Expenditure Over Time.

• **Panel regression with two-way fixed effects**, controlling for country-specific and time-specific unobserved factors.
→ Common approach in cross-country growth and health studies *(Baldacci et al., 2004; Moreno-Serra & Smith, 2011)*.

• **FE estimators** → eliminate omitted variable bias due to country-specific heterogeneity *(Wooldridge, 2010; Baltagi, 2005)*.

• **Control variables** follow Barro-style growth regressions *(Barro & Sala-i-Martin, 2004)*.

Base model
FE* model with time and country fixed effects:

$$\log(\text{GDP}_{it}) = \alpha_i + \delta_t + \beta_1 \cdot \text{HealthExp}_{it} + \beta_2 \cdot \text{HealthExp}_{it}^2 + \gamma' X_{it} + \varepsilon_{it}$$

- $\log(\text{GDP}_{it})$: the natural logarithm of real GDP per capita for country i at time t,
- α_i: country-specific fixed effects,
- δ_t: captures time-specific effects,
- HealthExp_{it}: denotes either curative or preventive health spending as a share of GDP,
- HealthExp_{it}^2: squared term of either curative or preventive health spending,
- X_{it}: vector of controls
- ε_{it}: the idiosyncratic error term.

* We conducted Hausman test and test results supported the FE over the RE estimator

Endogeneity concern: *(Potential reverse causality)*

Real GDP per capita $\leftrightarrow$ Health expenditure

→ Used **lagged regressors** to reduce simultaneity bias:

$$\log(\mathrm{GDP}_{it}) = \alpha_i + \delta_t + \beta_1 \cdot \mathrm{HealthExp}_{i,t-1} + \beta_2 \cdot \mathrm{HealthExp}^2_{i,t-1} + \gamma' \mathrm{X}_{i,t-1} + \varepsilon_{it}$$

1st extension (adding income group):

$$\log(GDP_{it}) = \alpha_i^g + \delta_t^g + \beta_1^g \cdot Curative_{i,t-1} + \beta_2^g \cdot Curative^2_{i,t-1} + \gamma^{g\prime} X_{i,t-1} + \varepsilon_{it}$$

$g \in \{\text{low}, \text{high}\}$ indicates the income group

2nd extension (adding interaction with education expenditure):

$$\log(GDP_{it}) = \alpha_i + \delta_t + \beta_1 \cdot Curative_{i,t-1} + \beta_2 \cdot Curative^2_{i,t-1}$$
$$+\beta_3 \cdot \left(Curative_{i,t-1} \times Educ_{i,t-1}\right) + \beta_4 \cdot \left(Curative^2_{i,t-1} \times Educ_{i,t-1}\right) + \gamma' X_{i,t-1} + \varepsilon_{it}$$

Double or Debiased Machine Learning (DML) (Chernozhukov et al., 2018)

Goal: Estimate causal parameters (e.g., treatment effects) in high-dimensional settings while maintaining valid statistical inference.

Neyman Orthogonality: the estimating equations are locally insensitive to small errors in the ML step

Use **ML to flexibly model nuisance parameters**, such as control variables

"De-biases" estimates by **partialling out** the influence of covariates from both the treatment and the outcome.

Sample splitting — estimating nuisance functions on one fold and evaluating on another.

Result: Root-n consistent, asymptotically normal estimates of treatment effects

Partially linear regression*

$$Y_{it} = \beta D_{it} + \gamma D_{it}^2 + g\left(X_{it}, X_{it}^2, X_{it}^3, X_{it}X_{jt}, \bar{X}_i, \bar{X}_t\right) + \varepsilon_{it},$$

- Y_{it}: the log of real GDP per capita,
- D_{it}: health expenditure (curative or preventive),
- D_{it}^2: nonlinear term (quadratic) of health expenditure
- $g(\cdot)$: high-dimensional, nonparametric function of covariates and their nonlinear transformations and interactions,
- X_{it}^2, X_{it}^3: higher order transformations
- $\bar{X}_i$ and $\bar{X}_t$: country and year means used to account for unobserved country and time heterogeneity
- ε_{it}: the idiosyncratic error term.

* Other specs (lagged, with both X_i^0 and Y_i^0, with X_i^0 only) estimated; not shown here.

Let Z_{it} be the full set of covariates (including interactions, transformations, and fixed effects).

Step 1: Estimating Linear Effect $\boldsymbol{\beta}$

Treat D_{it} as the treatment; absorb D_{it}^2 into controls.

Stage 1: Nuisance Estimation: $\hat{\ell}(Z_{it}, D_{it}^2) = E[Y_{it} \mid Z_{it}, D_{it}^2], \quad \hat{m}(Z_{it}, D_{it}^2) = E[D_{it} \mid Z_{it}, D_{it}^2]$

Stage 2: Residual Regression: $\tilde{Y}_{it} = Y_{it} - \hat{\ell}(Z_{it}, D_{it}^2)$, $\tilde{D}_{it} = D_{it} - \hat{m}(Z_{it}, D_{it}^2) \rightarrow \tilde{Y}_{it} = \beta \tilde{D}_{it} + \varepsilon_{it}$

Step 2: Estimating Nonlinear Effect $\boldsymbol{\gamma}$

Treat D_{it}^2 as the treatment; absorb D_{it} into controls.

First Stage: Nuisance Estimation: $\hat{\ell}(Z_{it}, D_{it}) = E[Y_{it} \mid Z_{it}, D_{it}]$, $\hat{m}(Z_{it}, D_{it}) = E[D_{it}^2 \mid Z_{it}, D_{it}]$

Second Stage: Residual Regression: $\tilde{Y}_{it} = Y_{it} - \hat{\ell}(Z_{it}, D_{it})$, $\tilde{D}^2{}_{it} = D_{it}^2 - \hat{m}(Z_{it}, D_{it}) \rightarrow \tilde{Y}_{it} = \gamma \tilde{D}^2{}_{it} + \varepsilon_{it}$

We employed 5 machine learning models to estimate nuisance functions $l(Z_{it}, D_{it})$and $m(Z_{it}, D_{it})$ under a cross-fitting scheme with K=5 folds. These learners are **Lasso, Ridge, Elastic Net Regression, Random Forest,** and **XGboost (boosted trees).**

Results - FE models for Curative

Summary of Table 4.2 : FE regressions for Curative Expenditure.

Model	Curative	Curative²	Controls	Lagged	R^2
OLS (1)	0.590***	–0.034***	No	No	0.244
FE with controls (3)	–0.195+	0.032**	Yes	No	0.295
FE Lag with controls (6)	**–0.175+**	**0.030****	**Yes**	**Yes**	**0.331**

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

→ Nonlinear U-shaped relationship of the curative spending and GDP per capita
→ Above **~2.87%** of GDP, curative spending starts to have a positive effect on GDP per capita
→ Pattern is similar in both contemporaneous and lagged FE models

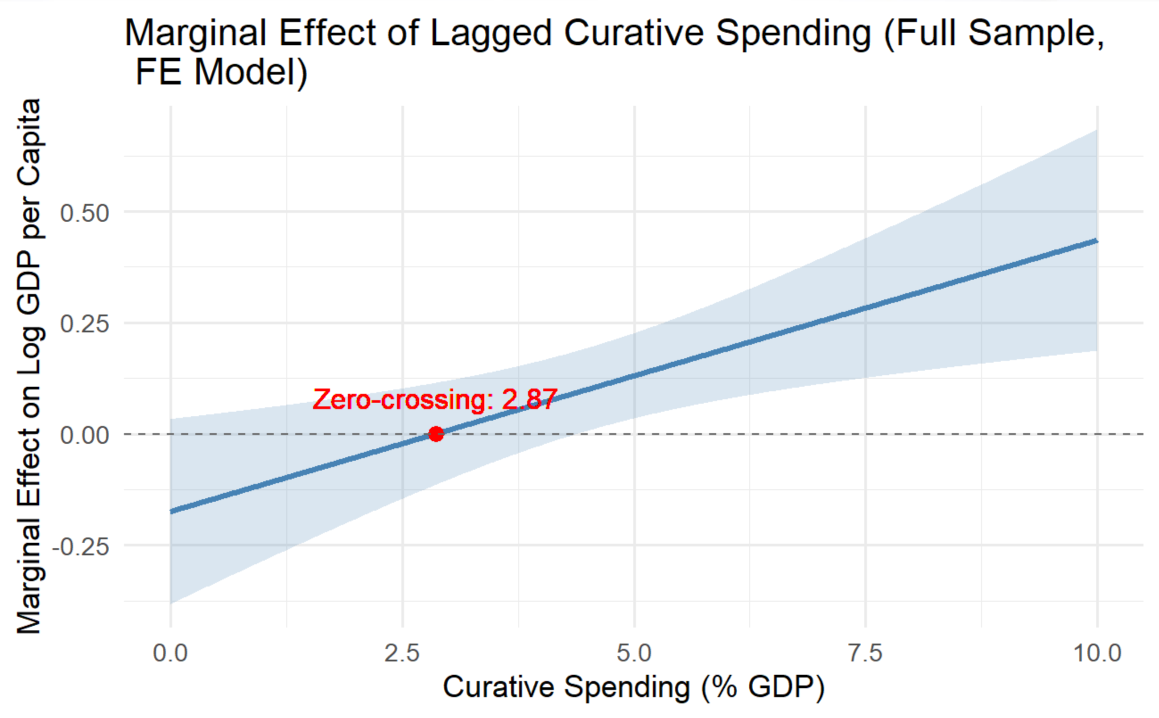

Figure 4.1 : Marginal Effect for Curative Expenditure, 95% CI bands.

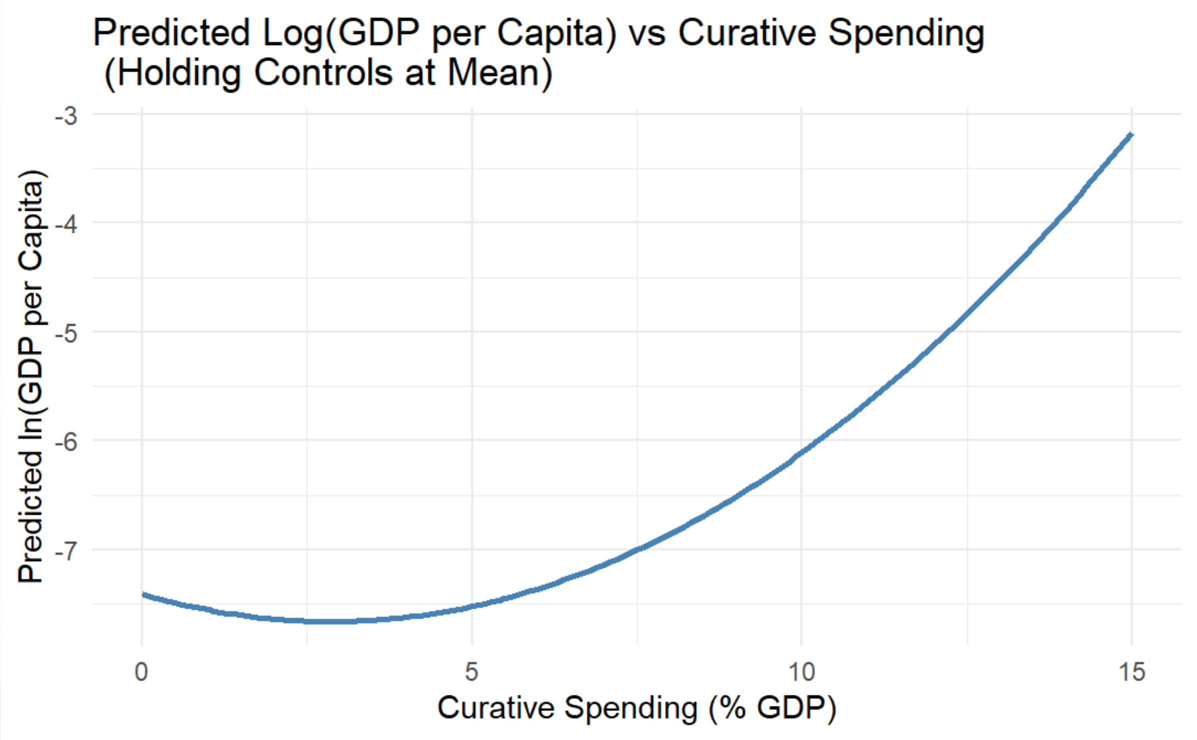

Figure 4.2 : Predicted Log of GDP per Capita and Curative Expenditure.

FE models for Preventive

Summary of Table 4.4 : FE Models for Preventive Expenditure.

Model	Preventive	Preventive²	Controls	Lagged	R^2
OLS (7)	**+1.971*** **	**–1.340*** **	No	No	0.056
FE with controls (9)	–0.317	**+0.378**	Yes	No	0.149
FE Lagged (12)	**–0.445**	**+0.672**	**Yes**	**Yes**	**0.191**

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

→ Preventive health expenditure shows **no significant relationship with GDP per capita** at 5% significance level when country-level heterogeneity and controls are accounted for.

→ **Possible reasons:** low variation in preventive spending, data quality limitations

Results - FE models for Preventive (Cont.)

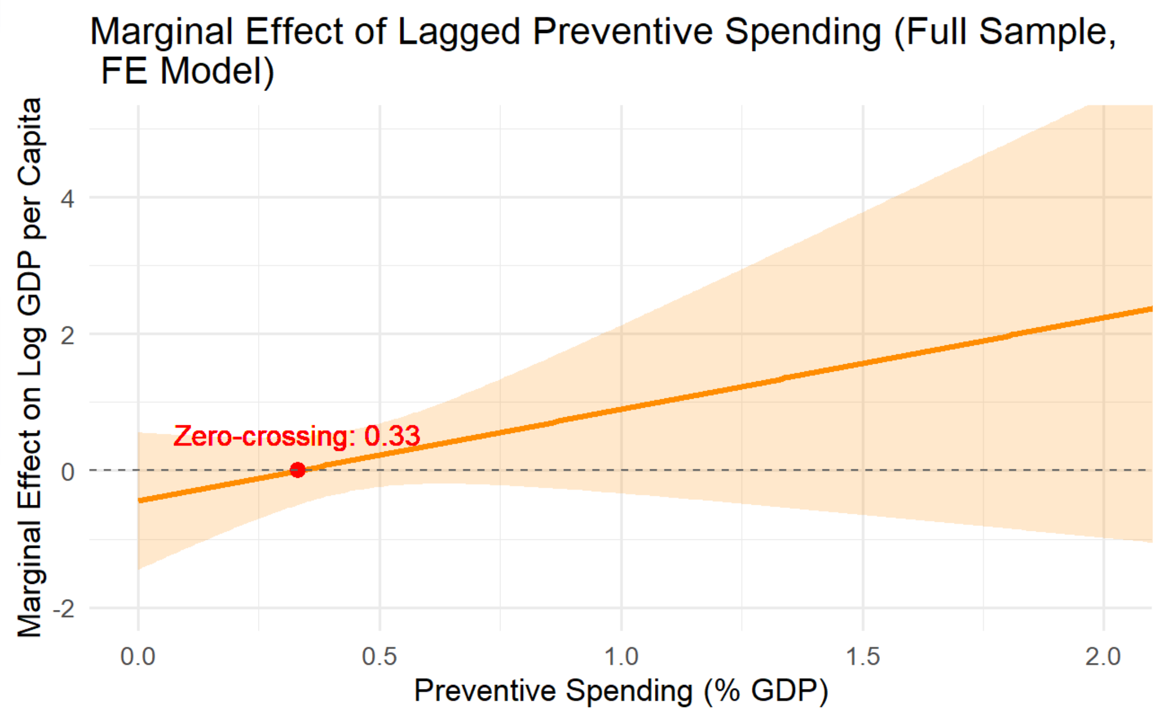

Figure 4.3 : Marginal Effect for Preventive Expenditure, 95% Confidence Bands.

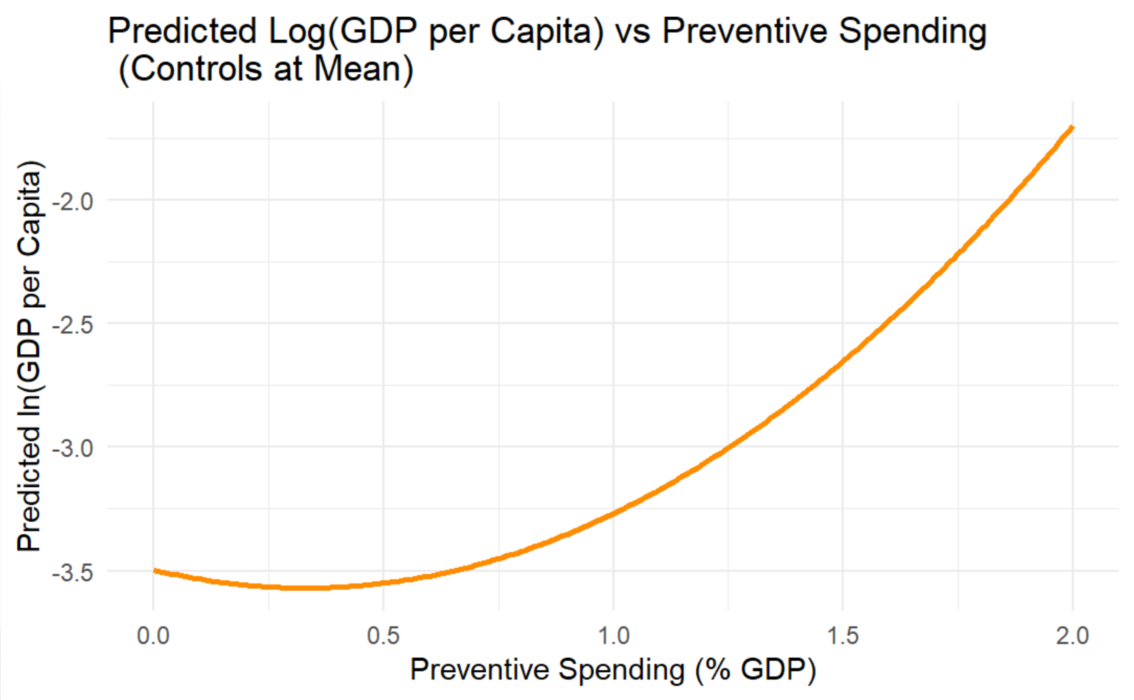

Figure 4.4 : Predicted Log of GDP and Preventive Expenditure (Holding Controls at Means).

Summary of Table 4.5 : Curative Expenditure - Decomposition by Income Groups.

Group	Curative	Curative²	R^2
Low Income	–0.075	0.025	**0.698**
High Income	**0.211*****	**–0.012+**	0.221

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The effect of curative spending varies by income level

- No significant effect in **low-income group*** (threshold 1.5% of GDP)
- Some evidence of nonlinear relationship in **high-income group*** (threshold ≈ 8.79% of GDP)

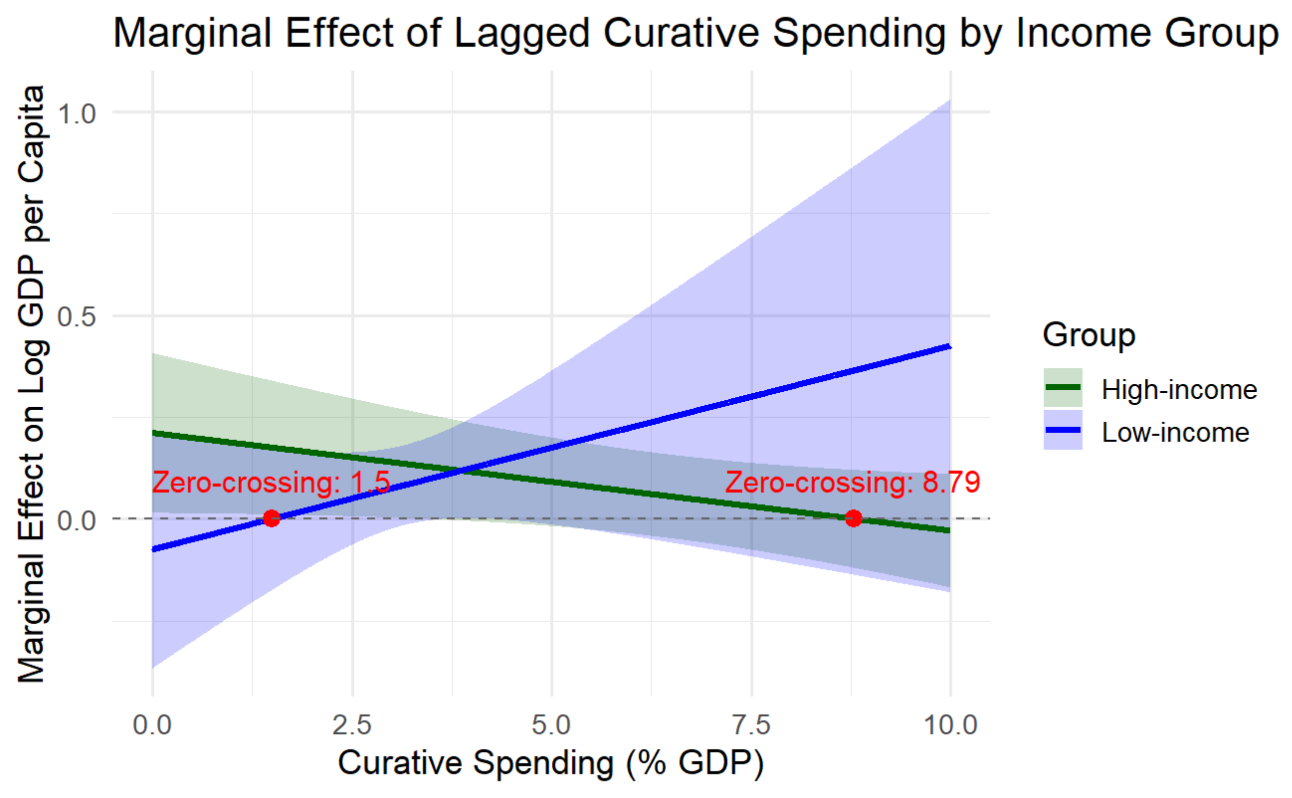

Figure 4.5 : Marginal Effect for Curative Spending by Income Group.

* Income groups were created based on the sample mean of real GDP per capita (relative classification)

Summary of Table 4.6 : Curative Expenditure - Decomposition by Education Expenditure.

Model	Curative	Cur²	Cur × Edu	Cur² × Edu	R^2
FE (17)	**–0.279***	**+0.053*****	0.011	**–0.003***	0.331
FE Lag (18)	**–0.283***	**+0.056*****	0.013	**–0.004***	0.367

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Education (% of GDP)	Turning point (Curative %)
1	2.72
4	3.53
7	5.05

- **In high-education countries, marginal returns to curative spending decline sooner**
- Reflects **faster diminishing returns** as education rises

Results - DML for Curative

Summary of Table 4.7 : Curative Expenditure - DML Estimates.

Curative Expenditure – Double ML****				
Model	**Curative**	**SE**	**Curative²**	**SE**
Lasso (CV)	0.0493	0.0998	0.0051	0.0094
Ridge (CV)	**0.1146*** **	0.0336	0.0057	0.0032
Elastic Net (.5, CV)	0.0325	0.0992	0.0037	0.009
Random Forest	0.0083	0.0517	0.0022	0.0038
XGBoost (Depth 4)	0.1630	0.0986	0.0069	0.0052
Best Performing Model	**0.1630**	**0.0986**	**0.0069**	**0.0052**
Least Squares Avg.	0.1561	0.1101	0.0070	0.0061

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

Summary of Table 4.8 : Lagged Curative Expenditure - DML Estimates.

Lagged Curative Expenditure – Double ML****				
Model	**Curative**	**SE**	**Curative²**	**Curative² SE**
Lasso (CV)	0.0261	0.1056	0.0081	0.0095
Ridge (CV)	**0.1141*** **	0.0312	**0.0074** **	0.0030
Elastic Net (.5, CV)	-0.0120	0.0987	0.0075	0.0091
Random Forest	-0.0018	0.0464	0.0006	0.0038
XGBoost (Depth 4)	0.1013	0.0720	**0.0069*** **	0.0022
Best Performing Model	**0.1013**	**0.0720**	**0.0069*** **	**0.0022**
Least Squares Avg.	0.0738	0.0643	0.0000	0.0037

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

**** In both tables we report the “only initial X specification”

Results – DML: Model Diagnostics

Summary of Tables 4.9-4.11

Model	RMSE_Y	RMSE_ Curative	RMSE_Cur²
XGBoost	**0.0805**	**0.0804**	**0.6104**
Random Forest	0.1097	0.1102	1.5382
Elastic Net (.5)	0.2113	0.2087	1.0849
Lasso (CV)	0.2058	0.2058	1.0541
Ridge (CV)	0.2453	0.2459	2.3507

→ **XGBoost outperforms all learners**
Lowest RMSE for Y, Curative, and Curative²

→**Ridge performs worst**: RMSE_Cur > 0.24, RMSE_Cur² > 2.35

→ **Tree-based models (XGBoost, RF) > Linear models (Lasso, Ridge) =** Better at capturing **nonlinear patterns**

→ **However ! Better fit ≠ more significant causal estimates**

Here we only discuss the contemporaneous models diagnostics

Results - DML for Preventive

Summary of Table 4.13 : Preventive Expenditure - DML Estimates.

Preventive Expenditure – Double ML****

Model	Preventive	SE	Preventive²	SE
Lasso (CV)	**0.7839*****	0.1356	**-0.4362****	0.1486
Ridge (CV)	**0.612*****	0.1467	-0.181	0.1057
Elastic Net (.5, CV)	**0.7785*****	0.1095	**-0.4065*****	0.1195
Random Forest	0.1543	0.1481	0.0214	0.0943
XGBoost (Depth 4)	-0.1842	0.1586	**-0.1315****	0.0507
Best Performing Model	-0.1842	0.1586	**-0.1315****	0.0507
Least Squares Avg.	0.2385	0.4484	0.0412	0.1951

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

Summary of Table 4.14 : Lagged Preventive Expenditure - DML Estimates.

Lagged Preventive Expenditure – Double ML****

Model	Preventive	SE	Preventive	SE
Lasso (CV)	**1.0669*****	0.1451	**-1.0583*****	0.1927
Ridge (CV)	**0.5417*****	0.1774	**-0.1168**	0.1937
Elastic Net (.5, CV)	**1.0736*****	0.1476	**-0.9589*****	0.1728
Random Forest	**0.3877*****	0.0771	**0.2380*****	0.0481
XGBoost (Depth 4)	**0.3763*****	0.0472	**0.2166*****	0.0089
Best Performing Model	**0.3763*****	0.0472	**0.2166*****	0.0089
Least Squares Avg.	0.2491	0.3882	0.0940	0.1011

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

→ Diminishing returns to preventive health spending
→ From Elastic Net optimal threshold is 0.95% of GDP

→ Models disagree
→ Linear models suggest inverted U-shape, with estimated turning point ≈ 0.504% of GDP
→ Tree-based model give unrealistic estimations

**** In both tables we report the “only initial X specification”

Summary of Tables 4.15-4.17

Model	RMSE_Y	RMSE_ Preventive	RMSE_ Preventive²
XGBoost	**0.0806**	**0.0147**	**0.0315**
Random Forest	0.1095	0.0397	0.0616
Elastic Net (.5)	0.2168	0.0533	0.0474
Lasso (CV)	0.2161	0.0536	0.0473
Ridge (CV)	0.2478	0.0527	0.0511

→ XGBoost again outperforms all learners

→RMSE’s are lower than for Curative DML models

→ Predicting the outcome variable remains the hardest task for our models

Here we only discuss the contemporaneous models diagnostics

💉 Curative Health Expenditure

→ Both methods confirm **nonlinear effect (convex U-shaped relationship =** benefits emerge after a threshold)
→ **DML estimates** are **smaller** in size but robust
→ Linear term: **both approaches conclude to be not significant**

🛡️ Preventive Health Expenditure

→ **FE:** no significant effects in both specifications
→ **DML: contemporaneous nonlinear effect,** for lagged version contradicting estimates. Most likely - concave (=benefits peak, then diminish)

⚠️ Limitations

- Endogeneity may still remain an issue (no IV or GMM)
- Measurement errors in health expenditure: Preventive spending data is noisy and inconsistent across countries/years
- OECD sample only — limited generalizability to low-income countries

🔬 Future Research Directions

- Apply instrumental variables or system GMM approach to address reverse causality/endogeneity problem
- Expand sample beyond OECD countries
- Test other sources of heterogeneity: two-way fixed effects versus interactive fixed effects

Context matters:

Positive economic effects appear only at a later threshold for high-income or high-education settings

In high education investment countries marginal returns decline sooner

Policy Implications

Health–education policy alignment

Efficiency benchmarks for health spending (GDP thresholds)

Improved classification/tracking of preventive spending

Curative health spending has a positive economic impact, but only **beyond a certain threshold** and with **a time lag**

Its effectiveness is depends on the income level of the country and education spending.

Thank you!

	OLS Curative (model 1)	FE Curative (model 2)	FE Control Curative (model 3)	OLS lag Curative (model 4)	FE lag Curative (model 5)	FE lag Control lag Curative (model 6)
Curative	0.590***	-0.061	-0.195+	0.607***	-0.056	-0.175+
	(0.058)	(0.156)	(0.117)	(0.058)	(0.150)	(0.106)
$Curative^2$	-0.034***	0.006	0.032**	-0.035***	0.005	0.030**
	(0.004)	(0.011)	(0.011)	(0.004)	(0.011)	(0.011)
Num.Obs.	648	648	648	621	621	621
Intercept	Yes	No	No	Yes	No	No
Controls included	No	No	Yes	No	No	Yes
Lagged controls	No	No	No	No	No	Yes
R2	0.244	0.007	0.295	0.253	0.007	0.331
R2 Adj.	0.242	-0.078	0.225	0.251	-0.081	0.264
AIC	1054.1	-646.3	-853.7	1001.5	-640.8	-872.7
BIC	1072.0	-632.9	-809.0	1019.2	-627.5	-828.4
Log.Lik.	-523.067			-496.754		
RMSE	0.54	0.15	0.12	0.54	0.14	0.12

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Heteroskedasticity-robust standard errors. Models 4-6 use lagged versions of variables, identical row labels are used for readability; see model specifications for details.

	OLS Preventive (model 7)	FE Preventive (model 8)	FE Control Preventive (model 9)	OLS lag Preventive (model 10)	FE lag Preventive (model 11)	FE lag Control lag Preventive (model 12)
Preventive	1.971***	-0.576	-0.317	2.115***	-0.741	-0.445
	(0.385)	(0.616)	(0.460)	(0.516)	(0.629)	(0.514)
$Preventive^2$	-1.340***	0.493	0.378	-1.499*	0.649	0.672
	(0.380)	(0.424)	(0.350)	(0.635)	(0.532)	(0.522)
Num.Obs.	648	648	648	621	621	621
Intercept	Yes	No	No	Yes	No	No
Controls included	No	No	Yes	No	No	Yes
Lagged controls	No	No	No	No	No	Yes
R2	0.056	0.019	0.149	0.056	0.025	0.191
R2 Adj.	0.053	-0.065	0.065	0.053	-0.061	0.109
AIC	1198.6	-653.9	-732.2	1147.1	-652.1	-754.3
BIC	1216.5	-640.5	-687.4	1164.8	-638.8	-710.0
Log.Lik.	-595.319			-569.537		
RMSE	0.61	0.15	0.14	0.61	0.14	0.13

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Heteroskedasticity-robust standard errors. Models 4-6 use lagged versions of variables, identical row labels are used for readability; see model specifications for details

Appendix – Curative & Income Level

	FE Control Curative Low Income (model 13)	FE Control Lag Curative Low Income (model 14)	FE Control Curative High Income (model 15)	FE Control Lag Curative High Income(model 16)
Curative	-0.055	-0.075	0.129	**0.211***
	(0.132)	(0.149)	(0.088)	(0.100)
Curative²	0.023	0.025	-0.004	**-0.012+**
	(0.020)	(0.022)	(0.005)	(0.007)
Life Expectancy	**-0.101***	**-0.107***	-0.009	-0.010
	(0.040)	(0.045)	(0.045)	(0.043)
Education Spending	**0.076***	0.060	**-0.042***	**-0.067****
	(0.035)	(0.037)	(0.019)	(0.024)
Population	**-0.064*****	**-0.063*****	-0.003	0.001
	(0.010)	(0.011)	(0.004)	(0.005)
Share of Population 65+	**-0.108***	**-0.115****	**-0.022+**	-0.015
	(0.042)	(0.036)	(0.012)	(0.013)
Trade	**0.005****	**0.006*****	0.000	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Savings Rate	0.007	0.007	**0.008***	**0.011***

\	FE Control Curative Low Income (model 13)	FE Control Lag Curative Low Income (model 14)	FE Control Curative High Income (model 15)	FE Control Lag Curative High Income(model 16)
Short-term Interest Rate	-0.003	-0.000	**0.041*****	**0.028****
	(0.009)	(0.009)	(0.009)	(0.009)
Num.Obs.	240	230	408	391
R2	0.665	0.698	0.202	0.221
R2 Adj.	0.596	0.634	0.095	0.114
AIC	-340.2	-361.2	-765.2	-742.6
BIC	-305.4	-326.8	-725.1	-702.9
RMSE	0.11	0.11	0.09	0.09

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Heteroskedasticity-robust standard errors. Models 14, 16 use lagged versions of variables, identical row labels are used for readability; see model specifications for details or refer to the full table in the Appendix

	FE Control Curative by Education (model 17)	FE Control Curative by Education (Lag) (model 18)
Curative	**-0.279***	**-0.283***
	(0.125)	(0.114)
Curative²	**0.053*****	**0.056*****
	(0.013)	(0.013)
Curative * Education Spending	0.011	0.013
	(0.012)	(0.012)
Curative² * Education Spending	**-0.003***	**-0.004***
	(0.002)	(0.002)
Life Expectancy	-0.070	-0.080
	(0.046)	(0.051)
Population	**-0.036*****	**-0.036*****
	(0.009)	(0.009)
Share of Population 65+	-0.028	-0.027
	(0.019)	(0.018)
Trade	0.002	**0.003+**
	(0.002)	(0.001)
Savings Rate	**0.008****	**0.010****
	(0.003)	(0.003)
Short-term Interest Rate	-0.004	-0.005
	(0.006)	(0.006)

	FE Control Curative by Education (model 17)	FE Control Curative by Education (Lag) (model 18)
Num.Obs.	648	621
R2	0.331	0.367
R2 Adj.	0.263	0.302
AIC	-885.6	-904.9
BIC	-836.4	-856.2
RMSE	0.12	0.11
Joint F-test: Interactions (F, df1, df2, p)	F = 11.35, df = (2, 588), p = 0.0000	F = 13.50, df = (2, 562), p = 0.0000

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Heteroskedasticity-robust standard errors. Model 18 uses lagged versions of variables, identical row labels are used for readability; see model specifications for details.