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THE ECONOMIC IMPACT OF ACADEMIC RESEARCH INSTITUTIONS: MEASURING CONTRIBUTIONS TO PRODUCTIVITY AND GROWTH

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Abstract: This study investigates how higher-education R&D relates to business R&D using fixed-effects panel regression with annual data from 1995 to 2024. A 1% increase in HERD is associated with ~0.3–0.35% rise in BERD over 1–2 years; point estimates are stable across timing yet imprecise under small-G wild-cluster bootstrap. First-differences and an error-correction model indicate modest short-run effects and medium-run convergence. A simple foreign-HERD measure is negative, and domestic elasticities are larger in high-intensity HERD settings. Instrumental variables are weak and dynamic GMM exploratory. Findings support medium-run associations and motivate sustained HERD where absorptive capacity is strong.

Keywords: Knowledge Spillovers, Fixed-Effects Panel Regression, Higher Education R&D, Business Enterprise R&D, Productivity

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1. Introduction (1 page)

Universities are central producers of frontier knowledge, and a long tradition in innovation economics argues that their research can catalyze private R&D through diffusion, talent mobility, and collaboration. We study this link by assembling an annual panel for 37 OECD countries over 1995–2024 (1,110 country–years) and asking whether higher-education R&D (HERD) crowds in business R&D (BERD). Our design compares each country to itself over time in log models with two-way fixed effects, explores timing (up to three lags), and reports inference that is conservative for a 37-cluster panel (wild-cluster pairs bootstrap).

The baseline estimates point to a meaningful medium-run elasticity—on the order of one-third: when HERD rises, BERD tends to rise over the following one to two years. First-difference and error-correction formulations show modest short-run responses and gradual convergence, and adding country-specific trends attenuates the one-year coefficient, consistent with co-movement building over several years rather than sharp annual spikes.

Extensions suggest a negative coefficient on foreign HERD—plausibly short-run input competition in global R&D markets—and a larger domestic association in high-intensity R&D environments, consistent with absorptive-capacity mechanisms. Instrumental-variables attempts based on deeper-lag macro shifters are weak, and dynamic-panel GMM is exploratory; we therefore emphasize fixed-effects associations.

A complementary TFP exercise does not detect robust one-year effects, pointing to a primary near-term channel via firm R&D. The paper details data construction, econometric strategy, results, and limitations, and maps priorities for sharper identification. The structure of the paper is outlined as follows. Section 2 reviews existing literature concerning university-to-industry knowledge transfer, as well as on the methodologies employed in prior studies. Section 3 outlines the data handling methods and descriptive statistics for our variables. Sections 4 and 5 present and discuss our methodology and alternative approaches, as well as the results. Finally, Section 6 identifies the study's main limitations and addresses paths for future research while Section 7 concludes by summarizing the key findings. An Appendix provides additional evidence to assist the analysis.

2. Literature Review

It is recognized that creating and applying new knowledge is the primary driver of economic growth, and universities are widely recognized as major sources of such knowledge, especially in science and technology. It is therefore crucial to clarify the mechanisms by which university science moves into the economy. The economic literature on university-to-industry knowledge transfer is commonly grouped into four categories: firm characteristics (absorptive capacity, organization, partnerships); university characteristics (licensing regimes, patenting incentives, equity policies); geography (localized spillovers and the spatial firm–university relationship); and channels of knowledge transfer (publications, patents, and related routes).

Firm Characteristics

This branch of research originates from Cohen and Levinthal (1990) who introduce absorptive capacity—the ability to recognize and exploit external knowledge— as a function of a firm's own R&D. Using a cross-section of U.S. manufacturing sector surveys, they regress R&D intensity—measured by the R&D-to-sales ratio—on measures of technological opportunity and appropriability, reporting OLS, GLS, and Tobit estimates. The results support their two predictions: first, relevance of basic science is more strongly associated with R&D intensity than applied science; second, the effect of increasing appropriability on R&D intensity is significantly greater in industries where applied science is especially relevant. They conclude that in-house R&D builds abortive capacity, making firms better able to assimilate and exploit new knowledge. Cockburn and Henderson (1998) build on this notion, adding that the degree to which firms are "connected" to universities is also important for utilizing knowledge spillovers. Lim (2000) restructures the above two concepts and argues that the absorptive capacity of firms is primarily a function of their connectedness, of which its investment in R&D is just one of several components.

University Characteristics

Papers in this area refer mostly to the Bayh-Dole Act of 1980 (Office of the Law Revision Counsel 2025), which granted universities the right to license inventions from federally funded research. The key question is how this reshaped university intellectual property (IP) policies, faculty commercialization incentives, and whether these incentives shifted the average type of research from basic toward more applied science. Henderson et al. (1998) investigate overall patent quality over 1965–1988. Using all university U.S. patents (1965–mid-1992), a 1% random sample of all U.S. patents, and the post-1974 patents that cite each set, they compare university patents with a random sample along two dimensions: "importance," measured by forward citations, and "generality," measured by the dispersion of citing patents across classes. Their data show that university patents were more cited and more general than a random sample, but that edge disappeared—suggesting Bayh–Dole increased patenting more than it raised the rate of commercially important inventions.

Geography in Terms of Localized Knowledge Spillovers

Works in this area measure how knowledge inputs and outputs co-move across area, with both the inputs/outputs and the geographic unit of analysis varying by study. The idea that a connection between universities and industries is crucial for the effective commercialization of knowledge is underscored by Jaffe (1989), who argues that regions improving their university research systems increase local innovation both by attracting industrial R&D and augmenting its productivity. His work explores geographically mediated "spillovers" by relating U.S. state-level corporate patents over time to industry R&D and university research efforts in a Griliches (1979) (modified Cobb-Douglas). Using U.S. state-level time series on patents registered at the

U.S. Patent Office (proxy for economically useful knowledge), corporate R&D, and university research, he finds that corporate patenting responds positively not only to private R&D but also to university research within the state, with effects concentrated within technical fields. At the same time, evidence on the role of simple geographic proximity is clouded: "There is only weak evidence that spillovers are facilitated by geographic coincidence of universities and research labs within the state" (Jaffe, 1989, p. 968), and the effect appears more clearly within technical areas than in the aggregate across areas, suggesting targeted rather than diffuse impacts of research universities. Extending the spatial lens, Jaffe et al. (1993) connect input original patents to output patents that cite the originals and examine how this link varies at the city level, while Audretsch and Feldman (1996) relate local university research funding to local industry value added at the state level, further documenting that the strength and localization of spillovers depend on both the type of input–output measure and the geographic scale.

Channels of Knowledge Transfer

This stream of research examines the channels transferring knowledge from universities to industry—publications, patents, consulting, informal meetings, recruiting, licensing, joint ventures, and personal exchange. Cohen et al. (1998) assess the perceived importance of these channels using a survey of U.S. manufacturing R&D lab managers finding wide sectoral variation and generally higher ratings for publications, conferences, informal conversations, and consulting than for patents or licensing. Using the same survey, Cohen et al. (2000) emphasize that publications, consulting, and open meetings/conferences dominate patent licensing and student recruiting. In a policy context, Bloom et al. (2019) review innovation instruments—R&D tax incentives, research grants, IP protection, human-capital investments, and pro-competitive policies—and argue that knowledge spillovers are a central market failure, with social returns to R&D persistently exceeding private returns, thereby justifying government support while recognizing IP trade-offs.

The literature discussed thus far provides a comprehensive understanding of knowledge transfer mechanisms and policy considerations. To motivate our empirical strategy, we draw on the framework by Moretti et al. (2019).They use two complementary longitudinal datasets—a country-industry-year level dataset for OECD countries and a firm-year-level dataset for France—to address two related questions.

Estimate the effect of government-funded R&D on private R&D—namely, whether government funded R&D in each country and industry displaces or fosters private R&D in the same country and industry. Second, having found evidence of a positive effect, they estimate how investment in R&D affects productivity. For both types of analysis, the work assesses whether the gains of public R&D investment are limited to a single country or spill over across several countries.

Leveraging predicted defense R&D as an instrument (national defense shifts interacted with fixed industry exposure) and rich fixed effects, they find crowding-in of private R&D, within-industry international spillovers, and positive productivity effects.

3. Data

Our dataset integrates three OECD sources—STAN (2025a), ANBERD (2025b), and MSTI (2025c)—and includes annual observations for 37 OECD countries over 30 years (1995-2024), resulting in a panel of 1,110 rows and 10 columns. Variables encompass BERD as the dependent variable, GERD, HERD as the primary independent, GDP as a key control, and others like NOE, PGO, VAP, and WAG serving as controls or instruments. A summary of the variables used is available in Appendix A.1. Variable labels clearly define BERD as business R&D (the outcome), HERD as higher education R&D (the spillover source). Before any transformation we quantify missingness, as it poses a significant challenge, ranking variables by the share of missing values and highlighting where gaps cluster along the country and year dimensions (See Appendix A.2).

Preprocessing mitigates these issues through a two-step, within-country imputation to retain the panel while preserving its time structure. First, we linearly interpolate gaps within each country's time series, which reduces missing variables and the remaining gaps are filled via group-wise medians (by country) and overall medians, achieving zero missing variables across numeric variables.

We replicate all specifications on an observed-only panel (no interpolation/median fill), results are reported in Appendix C (Figures 25-41). Estimates are broadly consistent in spirit but less precise and sometimes unstable—e.g., some TWFE HERD coefficients attenuate or even change sign—reflecting the smaller, more unbalanced sample and strict calendar lags that drop additional observations. Our main tables therefore report the interpolated panel and use the observed-only results as a sensitivity check.

The null of normality is rejected across the board, after we run Jarque–Bera tests, which motivates the use of natural logs in the analysis, to address skewness, help us stabilize variance and interpret coefficients as elasticities. Lags, specifically one-, two-, and three-year lags of the key R&D series are computed pre-logs to preserve temporal integrity, and intensity measures facilitate subgroup splits ; full diagnostics in Table 6 Appendix A.3.

Descriptive statistics (Table 5; Appendix A.3) indicate strong right-skewness and fat tails for BERD/HERD, with dispersion dominated by country size rather than outliers within countries. This also motivates the use of log transformations and a two-way FE design to purge level differences.

Our correlation diagnostics tell a clear story. In levels, the big aggregates mostly move together because of country size; after logging, the pattern is more informative. BERD remains closely tied to research spending ($\boldsymbol{\rho(BERD, HERD) \approx 0.96}$) and still correlates with macro scale, so we avoid cross-sectional interpretations. This is exactly why the main estimates use logs with country and year FE. For IV, PGO shows the right shape: weak correlation with BERD (ρ≈0.16) yet strong links to macro determinants like wages ($\boldsymbol{\rho \approx 0.91}$), supporting instrument relevance for HERD without predicting the outcome directly. Complete correlations are in Table 5; Appendix A.3.

Panel unit-root diagnostics on logged levels are mixed: Levin–Lin–Chu rejects a unit root for R&D aggregates while Im–Pesaran–Shin is less decisive; GDP looks non-stationary. We treat the series as highly persistent, estimate levels with two-way FE and lags, confirm robustness using first differences and estimate a dynamic GMM specification to address persistence.

In sum, these preliminaries align with OECD trends, where R&D spending has grown, with business sectors dominating but higher education providing foundational spillovers. Overall, preliminaries highlight positive HERD-BERD ties, data imbalances addressed via imputation, and need for panel methods to handle non-stationarity and fixed effects.

4. Methodology

4.1. Main Regression

In order to evaluate the spillover effects of Higher Education R&D (HERD) on Business Enterprise R&D (BERD) we run a two-way fixed-effects (TWFE) regression that compares each country to itself over time, while controlling for any world-wide year shocks.

The dependent variable is the logarithm of business enterprise R&D, $\ln{(\text{BERD})_{i,t}}$. The regressor of interest is the logarithm of higher-education R&D measured either contemporaneously or at lags $k \in \{1,2,3\}$, written $\ln{(\text{HERD})_{i,t-k}}$. Controls capture macro scale and cost conditions with $\ln{(\text{GDP})_{i,t}}$, $\ln{(NOE)_{i,t}}$ (number of employees), $\ln{(VAP)_{i,t}}$ (value added) and $\ln{(WAG)_{i,t}}$ (wages and salaries). All variables are log-transformed so coefficients are elasticities and to mitigate skewness typical in cross-country R&D series. The baseline specification reads as follows:

$$\ln(BERD)_{i,t} = \beta_k \ln(HERD)_{i,t-k} + \Gamma' X_{i,t-1} + \alpha_i + \delta_t + \varepsilon_{i,t} \qquad (1)$$

Country fixed effects, α_i, purge time-invariant national characteristics—institutions, long-run innovation culture, structural industrial mix—that could confound levels and year fixed effects, δ_t, absorb global shocks such as technology waves or business cycles that hit all countries at once.

We first estimate a contemporaneous model ($k = 0$) to capture immediate crowd-in or crowd-out effects and then we re-estimate the model with $k = 1$, $k = 2$ and $k = 3$ to infer about delayed transmission consistent with budgeting cycles, hiring, and project formation between universities and firms. Finally, we estimate a distributed-lag specification including all lags simultaneously, delivering a cumulated elasticity that is economically interpretable as the total response over a three-year window.

Baseline uncertainty is computed with heteroskedasticity- and autocorrelation-robust standard errors clustered by country, which secure against serial correlation in long panels. Moreover, as the number of clusters is modest (37), we complement these with country-cluster pairs-bootstrap p-values (resampling countries, $B = 9{,}999$, two-sided percentile) and treat the bootstrap p-values as our primary significance metric. The goal is to avoid the downward-biased standard errors from treating observations as independent and reduce small-cluster distortions in inference.

We summarize the country effects themselves as we formally compare fixed effects against random effects with a Hausman test (favoring FE), Figures 4 & 5 in Appendix A.4.1 plot the estimated country fixed effects α_i, showing large, persistent cross-country differences in baseline BERD even after conditioning on covariates.

To round out the fixed-effects family, we add two small, within-FE extensions that are direct perturbations of equation (1). First, we infer about international spillovers by adding a lagged foreign HERD term— the log of the average HERD of all other countries (country i excluded), lagged one year—entered alongside the usual lagged domestic HERD and controls; estimation remains two-way FE.

Second, we probe heterogeneity by R&D environment by allowing the domestic HERD coefficient to vary with a country's baseline HERD intensity. These are descriptive extensions (not new identification strategies): the foreign term speaks to cross-border diffusion, while the intensity interaction asks who responds more. Full equations and results are reported in the Extensions section.

4.2. Robustness Checks

We stress-test the fixed-effects estimate of how ln $(BERD)$ responds to ln $(HERD)$ with two complementary checks that ask whether the FE elasticity survives the removal of trends and reallocations of the HERD timing.

First, we re-estimate the relationship using first differences (FD) which removes each country's fixed component and any country-specific linear trend, so what's left is the co-movement in changes, and —together with year dummies—captures broad global shocks and provides a directional check on the baseline elasticity:

$$\Delta ln(BERD)_{i,t} = \delta \Delta ln(HERD)_{i,t-1} + \theta' \Delta Z_{i,t-1} + \alpha_i + \delta_t + u_{i,t} \quad (2)$$

The specification includes year fixed effects in first differences (δ_t) and uses differenced controls $\Delta Z_{i,t-1}$.

In this setting the one-year lagged $ln\,(HERD)$ coefficient is essentially zero and imprecise (**bootstrap p-value: 0.743**). When we widen the horizon, a small positive effect shows up at two years ≈ **0.06** (**SE: 0.028**; **bootstrap p-value: 0.531**), but the three-year estimate is again imprecise (**bootstrap p-value: 0.996**). Fit is very low in all FD models, which is expected because differencing removes most of the slow-moving signals and amplifies noise. The implication for our FE estimates is straightforward: FD does not provide strong confirmation of the FE elasticity at the one-year frequency, but it also does not overturn it; if anything, it suggests that any spillover is modest and operates over longer horizons. (See Figures 6 to 9; Appendix A.4.2)

As we will see in our Results section, there is a FE–FD gap consistent with long-run cointegration relationships rather than short-run spillover effects. If BERD and HERD share a long-run equilibrium, FE in levels loads on that medium-run co-movement, whereas FD differences strip those slow components and leave small short-run signal. In fact, in Figure 10 Appendix A.4.2, we add country-specific linear trends to our TWFE model reduces the one-year elasticity of BERD with respect to HERD from ≈ **0.324** in the baseline to ≈ **0.187** (**SE: 0.12**; **bootstrap p-value: 0.989**), rendering it statistically indistinguishable from zero. This behavior is exactly what we would expect if the levels specification was capturing medium-run co-movement between university and private R&D (a cointegrating relation). In other words, once we purge country-specific drifts, the one-year impact is modest.

Furthermore, to directly test this, in Appendix B, we run an Error Correction Model (ECM). The short-run elasticity of BERD with respect to HERD is modest (**≈0.16**), while the lagged deviation from the long-run relation enters strongly negative (**≈−0.10**), implying convergence toward equilibrium with a half-life of **6.3 years**. This pattern—small impact term with significant error correction—confirms that our TWFE levels estimates reflect medium-run co-movement rather than a sharp one-year spillover.

Second, we use two alternative lag structures, a distributed lag structure that infers if our within-country elasticity is stable when we allow the response to be distributed along current and one-year lagged $\ln(HERD)$ and a 3-year moving-average of $\ln(HERD)$ that smooths idiosyncrasies in the annual HERD series and emphasizes the underlying medium-run movement rather than noisy single-year bumps:

Distributed-lag FE:

$$ln(BERD)_{i,t} = \beta_0 ln(HERD)_{i,t} + \beta_1 ln(HERD)_{i,t-1} + \Gamma' X_{i,t-1} + \alpha_i + \delta_t + \varepsilon_{i,t} \qquad (3)$$

Moving-average FE

$$ln(BERD)_{i,t} = \bar{\beta} ln(HERD\_ma3, i, t-1) + \Gamma' X_{i,t} - 1 + \alpha_i + \delta_t + \varepsilon_{i,t} \qquad (4)$$

with

$$ln(HERD\_ma3, i, t) = \frac{1}{3}\left[\ln(HERD)_{i,t} + \ln(HERD)_{i,t-1} + \ln(HERD)_{i,t-2}\right] \qquad (5)$$

The alternative-lag specs line up with the baseline. In the distributed-lag FE, the effect is split across t and $t-1$ about ≈ **0.195** (**S.E: 0.067**) contemporaneously and ≈ **0.156** (**S.E: 0.066**) at one year, implying a cumulative elasticity $(\boldsymbol{\beta_0} + \boldsymbol{\beta_1})$ ≈ **0.35**—virtually identical to the single-lag FE. The 3-year moving-average of ln $(HERD)$, yields an elasticity around **0.336** (**S.E: 0.083**). However, once we use country-cluster bootstrap p-values, these effects are not statistically distinguishable from zero (single-lag ≈ **0.975**; distributed-lag p for the contemporaneous term ≈ **0.966**; MA3 ≈ **0.995**). The message is that our within-country elasticity is not sensitive to how we time HERD, but precision is limited when we guard against over-rejection. The separate p-value for the distributed-lag $t-1$ term is not reported because the parameter is not well identified in the bootstrap due to collinearity. This stability of point estimates across lag structures suggests a stable medium-run association consistent with crowd-in, but not statistically distinguishable from zero under our small-G-robust bootstrap. (See Figure 11 Appendix A.4.2)

4.3. Extensions to the Fixed Effects Specification

We address cross-country spillovers by augmenting equation (1) with a country-external research term. For each country–year pair we construct the foreign HERD as the average HERD of all other countries (country $\boldsymbol{i}$ excluded), take logs, and lag one year and then we re-estimate the two-way FE model including both the usual lagged domestic $\mathbf{ln}\,(\boldsymbol{HERD_{i,t-1}})$ and the lagged foreign term, along with the lagged controls and clustered standard errors.

In Figure 12 (Appendix A.4.3), we have that the domestic elasticity is essentially the same as the single-lag FE estimate without the foreign term $\approx \mathbf{0.305}$ (**S.E: 0.034**). By contrast, the coefficient on lagged foreign HERD is negative about $\approx \mathbf{-4.36}$, (**S.E: 1.67**) but neither the domestic nor the foreign term is statistically different from zero under our country-cluster bootstrap (**p-value: 0.955** and **p-value: 0.885**, respectively). The domestic and foreign regressors are only weakly correlated in our data ($\boldsymbol{\rho} \approx \mathbf{0.21}$), so the negative foreign coefficient is not an artifact of near collinearity with domestic HERD. A negative coefficient on foreign HERD may be consistent with global input competition: if R&D labor and specialized research capacity are internationally mobile and inelastically supplied in the short run, an expansion of university research abroad can pull researchers, projects, and complementary private R&D away from the domestic economy, crowding out local BERD; but as we use a raw average that ignores economic links (trade, collaboration, geography) and is also potentially endogenous, we interpret the foreign coefficient cautiously.

University R&D may translate into business R&D only where firms have enough absorptive capacity Cohen and Levinthal (1990)—a thick R&D base, skilled labor, and complementary assets. To examine this heterogeneity without changing identification, we keep the same TWFE design and compare elasticities across two environments defined by the sample-median of HERD intensity. We use HERD intensity (HERD as a share of GDP) as proxy for country's R&D environment, compute the overall sample median of HERD intensity (across all country–years) and split the panel into two groups, a high intensity group corresponding to observations with $HERD\ intensity\ \geq\ median$ and a low intensity group corresponding to observations with $HERD\_intensity\ <\ median$.

The same two-way FE model as the baseline is re-estimated—same lagged domestic $ln(HERD)$, same lagged controls $X_{i,t-1}$, country fixed effects α_i, year fixed effects δ_t, and country-clustered SEs—separately for each subsample. This keeps coefficients directly comparable.

Formally, the two split-sample regressions are:

$$\ln\ BERD_{it} = \beta^H \ln\ HERD_{i,t-1} + \Gamma^{H'} X_{i,t-1} + \alpha_i + \delta_t + \varepsilon_{it} (i,t) \in \mathcal{H} \quad (6)$$

and

$$\ln\ BERD_{it} = \beta^L \ln\ HERD_{i,t-1} + \Gamma^{L'} X_{i,t-1} + \alpha_i + \delta_t + \varepsilon_{it} (i,t) \in \mathcal{L} \quad (7)$$

where $\mathcal{H}$ and $\mathcal{L}$ denote the high- and low-intensity sets.

The elasticity in the high-intensity group, $\widehat{\boldsymbol{\beta}}_{\mathcal{H}} = \mathbf{0.226}$ (**S.E: 0.0667**); however, the country-cluster bootstrap p-value yields **0.973**, so we do not reject zero under small-G-robust inference. The low-intensity estimate, $\widehat{\boldsymbol{\beta}}_{\mathcal{L}} = \mathbf{-0.079}$ (**S.E: 0.049; bootstrap p-value: 0.952**), is not significant by either method. Other controls behave similarly across groups, and within-R^2 remains modest in both. (see Figure 13; Appendix A.4.3) Interpreted alongside the pooled FE result, the pattern suggests that most average elasticity is largely driven by high-intensity countries, while low-intensity countries show little immediate response.

Under small-G-robust inference, however, the high-intensity coefficient is imprecisely estimated and not statistically different from zero, so we view this as descriptive heterogeneity rather than a sharp difference in effects. The evidence suggests absorptive capacity matters—firms in advanced economies better leverage university R&D but we refrain from causal claims.

4.4. Identification & Threats to Validity

Society–industry collaboration has gained prominence in recent years and is viewed as a key driver of countries' economic development, extending to entrepreneurial research and innovations that benefit society Audretsch et al. (2025). As in Moretti et al. (2019), our equation

(1) controls shocks that affect private R&D and may correlate with university R&D; two-way fixed effects absorb time-invariant country heterogeneity and common global shocks. However, they do not eliminate time-varying, country-specific shocks that can simultaneously move university budgets and firm R&D, as this type of expenditure is unlikely to be random. Variation in university R&D may reflect governments adjusting university budgets to sectoral conditions, universities targeting funds toward regions or fields facing shocks, and firms re-optimizing R&D plans in partly unobserved ways; thus, university R&D may contain an endogenous component.

4.5. IV Estimation

To address endogeneity arriving from the fact that university budgets and private R&D may react to common shocks (e.g., reverse causality: high BERD demands more HERD) we estimate an IV/2SLS version of the lag-1 model that treats $\ln(\mathrm{HERD}_{i,t-1})$ as endogenous and instruments it with deeper-lag macro shifters that act as budgetary drivers rather than direct determinants of current firm R&D.

Our specification uses $t-2$ macro shifters as instruments for HERD at $t-1$. The $t-2$ variables are good at predicting next year's HERD (relevance), but—once we control for country dummies, year dummies, and the $t-1$ macro controls—they should not directly move firms' HERD at t (exogeneity).

The first stage regresses $\ln(HERD_{i,t-1})$ on the instrument vector $Z_{i,t-2}$, the control vector $X_{i,t-1}$, and the same country and year fixed effects as the baseline:

$$\ln\left(HERD_{i,t-1}\right) = Z'_{i,t-2}\,\pi + \Gamma' X_{i,t-1} + \alpha_i + \delta_t + v_{i,t} \qquad (8)$$

The second stage replaces $\ln(HERD_{i,t-1})$ with its fitted value from the first stage in equation (1):

$$\ln\left(BERD_{i,t}\right) = \beta^{IV} \ln\left(\widehat{HERD}\right)_{\iota,t-1} + \Gamma' X_{i,t-1} + \alpha_i + \delta_t + \varepsilon_{i,t} \qquad (9)$$

We use lagged macro shifters $Z_{i,t-2}$ (e.g., ln PGO, ln VAP, ln WAG) as predictors of ln $(HERD_{i,t-1})$ conditional on country effects α_i, year effects δ_t, and controls $\Gamma' X_{i,t-1}$. The exclusion restriction is that, once we condition on α_i, δ_t and $X_{i,t-1}$, these $t-2$ shifters affect current private R&D only through their effect on next year's university R&D—not directly through today's business R&D decisions. Intuitively, they proxy medium-run public-budget and cost conditions that shape university funding, while any remaining contemporaneous effects on firms are absorbed by the controls and fixed effects. This model is tested and discussed in the Results section below. (See Figure 19; Appendix A.4.5)

4.6. Generalized Method of Moments

Private R&D is highly persistent as today's value of BERD partly reflects yesterday's BERD because projects span years, hiring and contracts adjust slowly, and budgets are sticky. By including ln $(BERD_{i,t-1})$ on the right–hand side, to reflect this gradual adjustment, our plain fixed effects estimator becomes biased (Nickell bias)[1]. Dynamic panel GMM (Arellano–Bond / Blundell–Bond) uses internal lags of the variables as instruments to identify the persistence parameter ρ and the elasticity of BERD with respect to university R&D, while controlling for fixed effects and allowing regressors to be endogenous or predetermined.

We keep the lag in the model, so we still allow persistence, but we instrument ln $(BERD_{i,t-1})$ with older lags that are correlated with ln $(BERD_{i,t-1})$ but not with today's error. Concretely, the dynamic specification we estimate is:

[1] Nickell (1981) defines Nickell bias as the finite-T bias that arises when estimating a dynamic panel with unit fixed effects, e.g. $y_{it} = \rho\, y_{i,t-1} + \alpha_i + u_{it}$, as $N \to \infty$ with T fixed. The within (FE/LSDV) estimator of ρ is biased of order $O(1/T)$ because $y_{i,t-1}$ remains correlated with the transformed error term after removing α_i. For $\rho > 0$ the bias is typically negative (downward), and a common approximation in the AR(1) case is Bias$(\hat{\rho}_{FE}) \approx -\frac{1+\rho}{T-1}$

$$\ln(BERD_{i,t}) = \rho \ln(BERD_{i,t-1}) + \sum_{k=1}^{3} \beta_k \ln(HERD_{i,t-k}) + \Gamma' X_{i,t-1} + \alpha_i + \delta_t + \varepsilon_{i,t} \tag{10}$$

We estimate two dynamic-panel GMM implementations. First, a Difference GMM (Arellano–Bond) that differences the equation to remove country fixed effects, treats the lagged dependent variable, $\ln(BERD_{i,t-1})$, as endogenous, and instruments it with deeper lags in levels; in this specification, $\ln(HERD_{i,t-1})$ and controls enter as predetermined. Second, a System GMM (Arellano–Bover/Blundell–Bond) that stacks difference and level equations, using internal lags for both $\ln(BERD_{i,t-1})$ and $\ln(HERD_{i,t-1})$: lagged levels instrument the differenced equation and lagged differences instrument the level equation (implemented with forward-orthogonal deviations and two-step robust covariance). Diagnostics diverge. In Difference GMM with collapsed, short-lag instruments, AR(1) is significant (as expected after differencing) while AR(2) is not, and the Sargan test fails to reject, so the instrument set is admissible; yet coefficients are fragile—very high persistence and an insignificant, even slightly negative, one-year HERD effect—so the safe takeaway is strong BERD persistence with no clear short-run HERD effect once dynamics are modeled. In System GMM, AR(2) does not reject but Sargan strongly rejects, rendering those estimates invalid for inference. We therefore regard Difference GMM as admissible but fragile, System GMM as invalid, and center conclusions on the FE and IV results, reporting GMM as a transparent dynamic complement. (See Appendix A.4.6; Figures 21 & 22)

4.7. TFP Analysis with Lagged HERD

To connect R&D movements to an economically meaningful outcome, we construct country–year total factor productivity (TFP) growth and relate it to lagged university and business R&D. We first build a Solow-residual measure of TFP from value added, employment, and prices, then relate it to lagged HERD and BERD in a two-way FE framework. Coefficients are elasticities: θ tells us the percentage change in TFP associated with a 1% increase in last year's university R&D (holding country/year effects and macro controls fixed), and ϕ does the same for firm R&D. The one-year lag targets near-term spillovers; country and year fixed effects take care of time-invariant national traits and common global shocks, so we focus on within-country movements. We proxy Total Factor Productivity as a Solow-residual using a Cobb–Douglas production function with real value added ($VAP_{i,t}$), employment ($NOE_{i,t}$), gross fixed capital stock ($PGO_{i,t}$) and a fixed labor share $\boldsymbol{\alpha = 0.6}$:

$$TFP_{i,t} = \ln (VAP)_{i,t} - \alpha \ln(NOE)_{i,t} - (1-\alpha)\ln (PGO)_{i,t} \qquad (11)$$

We then estimate a two-way fixed-effects model with lagged covariates:

$$TFP_{i,t} = \theta \ln (HERD)_{i,t-1} + \phi \ln (BERD)_{i,t-1} + \gamma_1 \ln (GDP)_{i,t-1} + \gamma_2 \ln (WAG)_{i,t-1} + \alpha_i + \delta_t + \varepsilon_{i,t} \qquad (12)$$

The estimated elasticity of TFP with respect to lagged HERD is small and negative, $\boldsymbol{\hat{\theta} \approx -0.015}$ (**S.E: 0.009**; **bootstrap p-value ≈ 0.881**), while the elasticity with respect to lagged BERD is small and positive, $\boldsymbol{\hat{\phi} \approx 0.013}$ (**S.E: 0.008**; not significant). By contrast, macro controls are strongly positive. Taken together, we do not find robust evidence that university R&D raises measured TFP at a one-year horizon once country/year effects and covariates are included; any direct HERD→TFP effect, if present, appears modest and statistically fragile. A reasonable interpretation is that HERD's main channel in the short run is to stimulate firm R&D (our BERD results), with productivity results arriving more slowly and being hard to detect in a noisy residual. (See Figure 23; Appendix A.4.7)

5. Results and Discussion

5.1. Cross Checks and Extensions

Over the previous sections we set out the core two-way fixed-effects (TWFE) design and a set of cross-checks and extensions. In sub-section 4.2, we saw that First-Differences show no precise one-year HERD→BERD response and only a small positive effect at $t-2$, and conclude that our levels specification was capturing medium-run co-movement between university and private R&D (a cointegrating relation) rather than a sharp short-run response.

Furthermore, our alternative timing specifications re-times the TWFE model in two different ways (distributed lags and a 3-year moving average of HERD) and got essentially similar medium-run magnitudes, reinforcing the baseline.

In sub-section 4.3, our spillover extension leaves the domestic elasticity intact once a foreign-HERD term is added, the foreign term is negative but imprecise, and because domestic and foreign HERD are only weakly correlated, this does not reflect collinearity. Additionally, the heterogeneity split between high and low HERD intensity countries, shows the effect concentrated in high-intensity R&D environments, consistent with absorptive-capacity differences.

Our initial goal with dynamic-panel GMM (sub-section 4.6) was to explicitly model persistence in BERD—by adding $\ln(\mathrm{BERD}_{i,t-1})$—and ask whether the HERD effect survives once we correct the Nickell bias using internal instruments. In practice, the diagnostics are mixed; Difference GMM clears the basic checks (AR(2) not rejected; over-ID acceptable) but the coefficients are fragile, while System GMM fails the over-identification test, making it not valid for inference. We therefore report GMM as exploratory and keep the TWFE and IV estimates as the results fit for inference.

Finally, the TFP exercise finds no robust one-year HERD→TFP effect once fixed effects and covariates are included, suggesting HERD's near-term channel is primarily via firm R&D rather than immediate productivity gains. With that landscape set, the rest of this section focuses on the main estimators TWFE and on IV quantifying magnitudes and comparing their implications.

5.2. TWFE & IV

The baseline two-way fixed effects models (country and year fixed effects) represent the cleanest identification strategy available in the data. The HERD coefficients are positive and economically sizable across contemporaneous and lag specifications, but under country-cluster pairs bootstrap they are not statistically significant (Table 1). The point estimates are stable across lags, indicating a rapid and persistent response in levels, but statistical power is limited with cluster-robust inference.

The fact that the contemporaneous coefficient (**0.335**) is very close to the one-year lag coefficient (**0.324**) suggests that private firms react quickly to expansions in academic research capacity (Appendix A.4.4, Table 13). This rapid response is consistent with several mechanisms: Universities training PhD students and post-docs who are immediately hired by industry, carrying cutting-edge knowledge with them; faculty consulting, joint labs, and collaborative projects generate almost immediate applied research opportunities for firms and new scientific instruments, datasets, and publications produced by universities become public goods that firms can exploit without substantial delay. The persistence of the effect through lag 3, with only modest attenuation, further indicates that the knowledge generated by universities has long-lasting value. Basic research findings often require several years to be translated into commercially relevant applications, yet firms appear to anticipate this future value and increase their own R&D spending accordingly.

With errors clustered by country—and especially with small-G-robust, country-cluster bootstrap p-values—the HERD coefficients are not statistically distinguishable from zero (**bootstrap p-values: 0.97–0.98** across lags). The loss of significance reflects limited degrees of freedom at the cluster level rather than a change in point estimates, which remain stable (**0.324** at lag 1, **0.278** at lag 2, **0.224** at lag 3). Policy interpretation should therefore emphasize the stable economic magnitude while acknowledging the imprecision.

Table 1: Robust TWFE Estimation with Clustered Errors

Model	Coefficient (lag HERD)	Clustered SE	t-stat	p-value	Bootstrap p-value
Lag 1 (m2)	0.324	0.206	1.57	0.116	0.975
Lag 2 (m3)	0.278	0.192	1.45	0.148	0.975
Lag 3 (m4)	0.224	0.171	1.31	0.190	0.968

The 2SLS-IV results present a puzzle at first glance: when instrumenting lagged HERD with two-year lags of PGO, VAP, and WAG, the coefficient flips dramatically negative (−1.9899) and imprecise. This result appears to contradict everything else in our work. However, a closer examination reveals that the instruments are extremely weak in this application.

Table 2: Comparison: OLS vs IV (2SLS) with FE

Variable	OLS	2SLS-IV
log_HERD_lag1	0.9372***	–1.9899
	(0.0376)	(0.9145)
log_GDP_lag1	0.2234***	2.2621*
log_NOE_lag1	–0.0597	–3.3553*
log_VAP_lag1	–0.0470**	–0.5056
log_WAG_lag1	0.1089***	1.0207*
Constant	–1.8614***	–22.5949
Observations	1,110	1,110
R^2	0.8655	–0.0859

PGO , VAP, and WAG are highly persistent aggregates that tightly co-move. Once we include country and year fixed effects, most of their variation is absorbed by those effects and so using two-year lags of these variables leaves little independent within-country movement, and the instruments are highly collinear with each other, which shows up as a weak first stage confirming dramatic weak-instrument problems (see Figure 19, Appendix A.4.5). The IV estimate is therefore essentially unidentified and should be disregarded. A weak instrument set does not validate the FE estimates; it only shows that our IV design does not isolate a plausibly exogenous component of HERD. Residual time-varying, country-specific shocks (e.g., a pro-innovation government elected in country i at time t boosting both university and business budgets) remain a potential source of bias for FE.

For clarity, the purpose of IV here was to provide relevant and exogenous variation in HERD after conditioning on fixed effects and controls, thereby clearing endogeneity from remaining shocks. Because our candidate instruments are weak in this setting, they do not deliver such variation.

6. Limitations & Further Research

This study sets a foundation for future analysis on the impact of university R&D on business R&D, an area of known importance. However, several limitations, primarily related to data availability, have constrained the depth of the analysis. Our results are shaped most of all by the data we could assemble. Coverage across countries and years is uneven, so we filled gaps by interpolating missing observations to keep the panel intact. Interpolation smooths real variation and can dampen short-run responses, which likely contributes to the strong persistence we estimate. With a small number of country clusters, conventional cluster-robust inference is fragile. We report wild-cluster bootstrap p-values to mitigate this, but precision remains limited and some patterns should be read with caution.

A second limitation is identification. Two-way fixed effects absorb time-invariant country traits and common global shocks, yet they cannot remove time-varying shocks that move university budgets and firm R&D at the same time. Our instrumental-variables attempts fail for weak first stages once fixed effects are included, and the dynamic-panel GMM checks are either fragile or fail standard diagnostics. As a result, we cannot rule out residual endogeneity or dynamic misspecification. The positive link we document between HERD and BERD is therefore best interpreted as a medium-run association rather than a clean causal effect.

A third limitation concerns how we measure foreign exposure. Our “foreign-HERD” term is a simple average of other countries’ HERD. This unweighted construct blends two forces that move in opposite directions: knowledge diffusion, which should raise domestic private R&D, and short-run input competition for researchers and specialized services, which can depress it. Without economically meaningful weights based on trade, technological proximity, or collaboration networks, we cannot separate these channels or give the foreign coefficient a clear interpretation.

These constraints suggest a direct agenda for future work. Extending the panel backward and forward—and broadening country coverage—would reduce the need for interpolation, strengthen statistical power, and lessen concerns about small-G inference even when we continue to bootstrap. Building a macro–micro bridge would allow sharper identification, linking country-level HERD to firm-level outcomes such as patenting and citation patterns, contract research with universities, or researcher mobility would enable event-study and difference-in-differences designs around plausibly exogenous funding shocks. These micro links would also help trace the timing of effects, from changes in university research activity to subsequent private R&D and, over longer horizons, to productivity growth.

Finally, integrating channel-specific heterogeneity is essential. Interacting HERD with measures of absorptive capacity, co-publication and co-patenting ties, and formal university–industry contracts would show where the elasticity is largest and through which channels. This would turn a broad association into a map of underlying mechanisms.

7. Conclusion

This work set out to measure how public research performed in universities (HERD) relates to private-sector R&D (BERD) across 37 OECD economies over 1995–2024. The evidence is clearest in the TWFE estimates, once we absorb time-invariant national traits and common global shocks, a 1% increase in HERD is associated with roughly a 0.3–0.35% rise in BERD over to two years. Point estimates are stable to re-timing (distributed lags, three- year moving average) but imprecise under small-G wild-cluster bootstrap, so we treat them as associations.

At the same time, the short-run response is modest. First-differences show little one-year movement and only a small effect at two years; the error-correction model reconciles the gap showing a modest short-run elasticity of BERD to HERD and a statistically meaningful speed of adjustment back toward a long-run relation. Adding country trends to TWFE similarly attenuates the one-year coefficient. In short, effects accumulate over time; differencing removes that slow signal and reveals little short-run response.

Two extensions sharpen the picture. First, the foreign-HERD term enters negatively but imprecise, consistent with short-run competition for globally mobile R&D inputs dominating over knowledge diffusion at annual horizons. We interpret this cautiously: a raw average is a blunt measure that mixes diffusion and competition and ignores economic weights (trade, technological proximity, collaboration networks). Second, the elasticity appears larger in high-HERD-intensity environments, countries with deeper research bases exhibit stronger firm responses, a pattern aligned with absorptive-capacity mechanisms. Together these results suggest that public research is most effective at crowding-in private R&D where complementary capabilities already exist and that internationally, ramp-ups abroad can, in the short run, pull inputs away.

Our IV strategy with instruments based on deeper-lag macro shifters are weak once we include rich fixed effects, so IV estimates are invalid for identification. Dynamic-panel GMM clears only the most basic checks in difference form and is fragile and system GMM fails over-identification. We therefore treat the TWFE and its variants as associational designs, not causal designs, and we base significance on country-cluster bootstrap p-values. A complementary TFP exercise finds no robust one-year HERD→TFP effect, suggesting a near-term operating primarily through business R&D, with any productivity impact likely slower and harder to detect in macro residuals.

Two limitations temper interpretation. First, missing data forced within-country interpolation plus medians to preserve panel structure, in observed-only runs, standard errors grow and some coefficients weaken, underscoring sensitivity to data coverage. Second, with 37 clusters, we report wild-cluster pairs-bootstrap p-values and note a few collinearity cases (e.g., split HERD levels and lags) where coefficient-wise bootstraps are not separately identified. These constraints are not fatal, but they bound what we can claim.

The policy reading is pragmatic. If the objective is to stimulate private R&D, sustained investment in higher-education research is associated with sizable medium-run increases in firm R&D, especially where research bases are deep. That points to stable, multi-year HERD funding, reinforcement of human-capital pipelines, and tighter university–industry ties where absorptive capacity is present but under-utilized. The negative foreign term reminds policymakers that global R&D markets are tight: to avoid short-run displacement, domestic investments should be paired with measures that retain and attract researchers (mobility programs, competitive salaries, shared infrastructure).

Overall, the study documents a robust medium-run association between public and private R&D and maps where it is likely strongest, while being explicit about identification limits. This combination—transparent design, rigorous robustness, and cautious language—provides a credible baseline for policy debates on how university research funding can support innovative capacity in the private sector.

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A Appendix

A.1 Variables Used

Table 3 : Summary of Variables Used and their Description

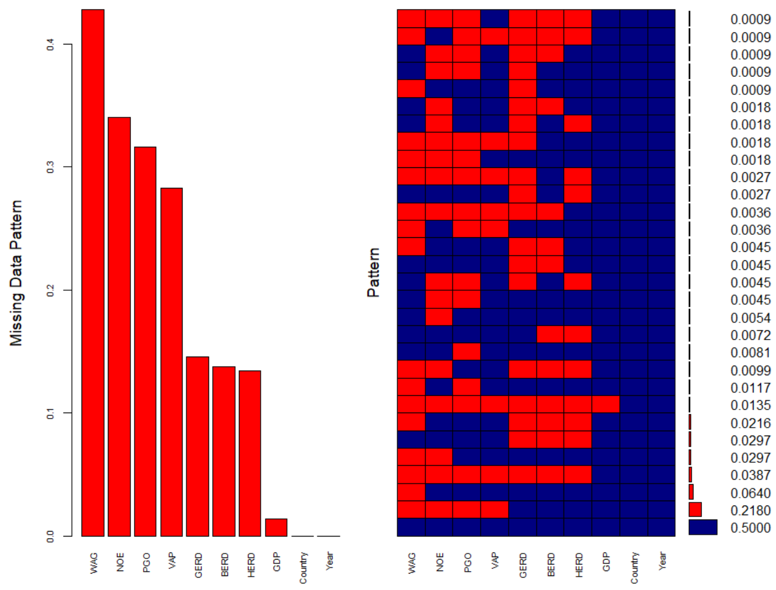
Variable Description	Variable Unit/Price basis
Business enterprise R&D expenditure (BERD)	Millions USD, current prices
Higher-education R&D expenditure (HERD)	Millions USD, current prices
Gross domestic expenditure on R&D (GERD)	Millions USD, current prices
Gross domestic product (GDP)	Millions USD, current prices
Number of employees (NOE)	Thousands of persons
Production gross output (PGO)	Millions USD, current prices
Value added (VAP)	Millions USD, current prices
Wages & salaries (WAG)	Millions USD, current prices

A.2 Missing Data Pattern

Table 4: Missing Data by Variable

Variable	Missing_Pct
WAG	42.79
NOE	34.05
PGO	31.62
VAP	28.29
GERD	14.59
BERD	13.78
HERD	13.42
GDP	1.35
Country	0.00
Year	0.00

Figure 1: Missing Data Pattern



A.3 Descriptive Statistics

Table 5: Summary Statistics by Variable

Variable	N	Mean	Median	SD	Min	Max	Skewness	Kurtosis
BERD	1110	20745.09	3245.45	65331.37	2.89	749390	6.85	61.19
GDP	1110	1228999.59	342283.24	2837887.28	6402.78	27720709	5.55	39.83
GERD	1110	29438.01	5654.00	86911.91	56.63	955578	6.49	54.60
HERD	1110	4877.64	1419.30	10604.52	0.94	102044	5.13	35.68
NOE	1110	11442.89	3544.40	23922.88	115.10	150263	4.19	21.74
PGO	1110	91110536.74	1904802.00	393521694.14	5845.60	3564095500	5.73	39.86
VAP	1110	41828537.66	900092.00	169939767.72	2452.70	1485899737	5.04	30.68
WAG	1110	10801054.54	319673.70	63138565.22	1104.30	626549800	6.73	49.89

Table 6: Jarque-Bera Normality tests

Variable	JB_Statistic	JB_PValue	Normal
BERD	165286.20	0	No
GERD	130941.49	0	No
HERD	54267.44	0	No
GDP	68458.37	0	No
NOE	19481.60	0	No
PGO	68907.51	0	No
VAP	40143.51	0	No
WAG	110079.13	0	No

Table 7: Correlation Matrix Key Variables

	BERD	GERD	HERD	GDP	NOE	PGO	VAP	WAG
BERD	1.000	0.998	0.963	0.971	0.870	0.161	0.182	0.086
GERD	0.998	1.000	0.975	0.981	0.887	0.149	0.171	0.078
HERD	0.963	0.975	1.000	0.982	0.905	0.102	0.123	0.031
GDP	0.971	0.981	0.982	1.000	0.927	0.108	0.128	0.042
NOE	0.870	0.887	0.905	0.927	1.000	0.153	0.183	0.042
PGO	0.161	0.149	0.102	0.108	0.153	1.000	0.984	0.905
VAP	0.182	0.171	0.123	0.128	0.183	0.984	1.000	0.867
WAG	0.086	0.078	0.031	0.042	0.042	0.905	0.867	1.000

Figure 2: Relationship between HERD and BERD (Log Scale)

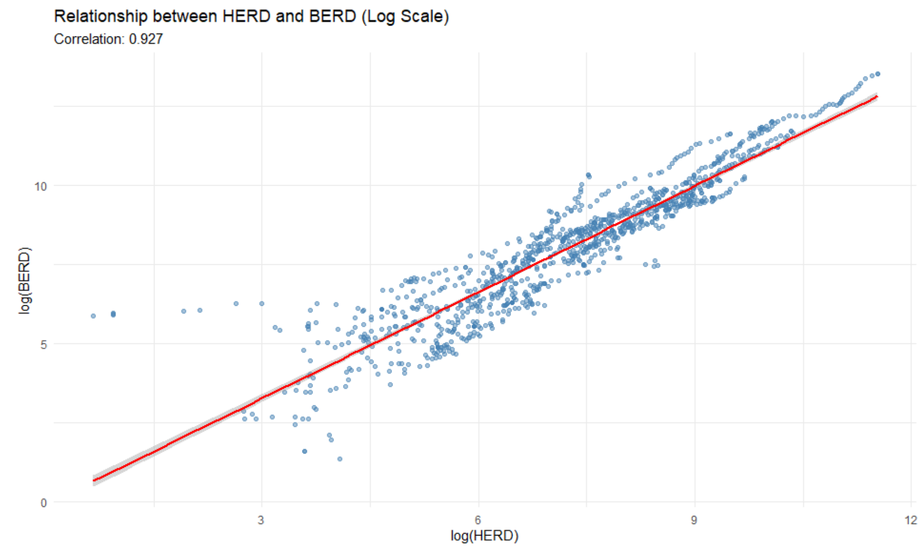


Figure 3: HERD-BERD Correlation Over Time

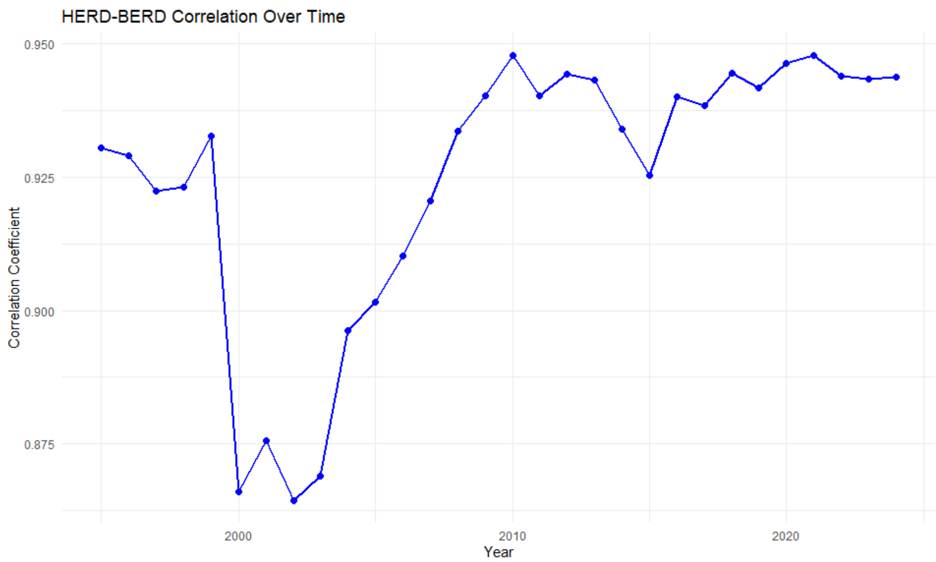


Table 8: Panel Unit-Root tests for $\ln(BERD)$

Test	Statistic	P-Value	Result
Levin–Lin–Chu	-3.2941	0.0005	Stationary
Im–Pesaran–Shin	1.6560	0.9511	Non-stationary

Table 9: Panel Unit-Root tests for $\ln(HERD)$

Test	Statistic	P-Value	Result
Levin–Lin–Chu	-7.1704	0.0000	Stationary
Im–Pesaran–Shin	-0.7031	0.2410	Non-stationary

Table 10: Panel Unit-Root tests for $\ln(GERD)$

Test	Statistic	P-Value	Result
Levin–Lin–Chu	-4.6424	0.0000	Stationary
Im–Pesaran–Shin	2.4775	0.9934	Non-stationary

Table 11: Panel Unit-Root tests for $\ln\ (GDP)$

Test	Statistic	P-Value	Result
Levin–Lin–Chu	-1.3727	0.0849	Non-stationary
Im–Pesaran–Shin	7.2171	1.0000	Non-stationary

A.4 Model Outputs

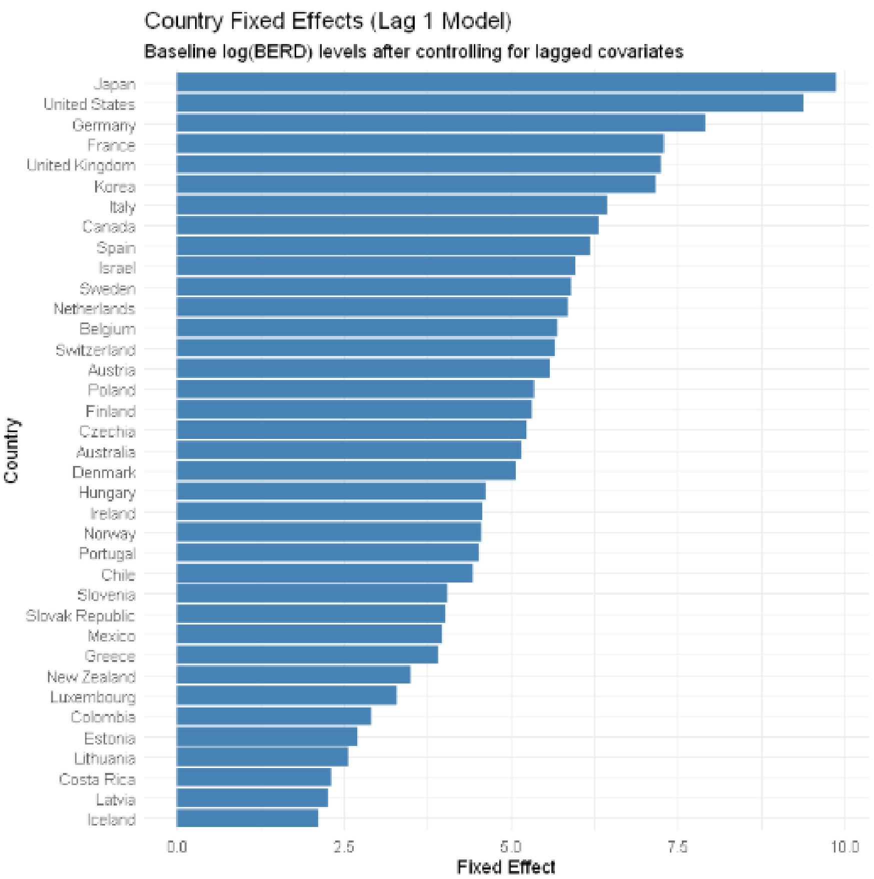
A.4.1 Country Fixed Effects

Figure 4: Hausman test Fixed Effects vs Random Effects

```
	Hausman Test

data:  log_BERD ~ lag(log_HERD, 1) + lag(log_GDP, 1) + lag(log_NOE,  ...
chisq = 40.834, df = 5, p-value = 1.014e-07
alternative hypothesis: one model is inconsistent
```

Figure 5: Country Fixed Effects



A.4.2 Robustness Checks

Figure 6: First-Differences with Lagged Independent Variables (Lag 1)

```
Oneway (individual) effect First-Difference Model

Call:
plm(formula = log_BERD ~ lag(log_HERD, 1) + lag(log_GDP, 1) +
    lag(log_NOE, 1) + lag(log_VAP, 1) + lag(log_WAG, 1), data = pdata_reg,
    model = "fd")

Balanced Panel: n = 37, T = 29, N = 1073
Observations used in estimation: 1036

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-1.5622944 -0.0591652 -0.0093276  0.0395900  1.6176518

Coefficients:
                   Estimate Std. Error t-value  Pr(>|t|)
(Intercept)       0.0590349  0.0074869  7.8851 7.977e-15 ***
lag(log_HERD, 1) -0.0046682  0.0276423 -0.1689   0.86593
lag(log_GDP, 1)   0.2066670  0.1144571  1.8056   0.07127 .
lag(log_NOE, 1)   0.0456934  0.1945606  0.2349   0.81437
lag(log_VAP, 1)  -0.0137234  0.0580222 -0.2365   0.81308
lag(log_WAG, 1)  -0.0240039  0.0647708 -0.3706   0.71101
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    23.737
Residual Sum of Squares: 23.655
R-Squared:      0.0034347
Adj. R-Squared: -0.001403
F-statistic: 0.70999 on 5 and 1030 DF, p-value: 0.61599

Bootstrap p-value [Δlog(HERD)_{t-1}] (country-cluster, B=9,999): 0.743
```

Figure 7: First-Differences with Lagged Independent Variables (Lag 2)

```
Oneway (individual) effect First-Difference Model

Call:
plm(formula = log_BERD ~ lag(log_HERD, 2) + lag(log_GDP, 2) +
    lag(log_NOE, 2) + lag(log_VAP, 2) + lag(log_WAG, 2), data = pdata_reg,
    model = "fd")

Balanced Panel: n = 37, T = 28, N = 1036
Observations used in estimation: 999

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-1.5637490 -0.0577950 -0.0096501  0.0392671  1.6127766

Coefficients:
                  Estimate Std. Error t-value Pr(>|t|)
(Intercept)       0.073129   0.007817  9.3551  < 2e-16 ***
lag(log_HERD, 2)  0.059949   0.027828  2.1543  0.03146 *
lag(log_GDP, 2)  -0.155973   0.118714 -1.3138  0.18920
lag(log_NOE, 2)   0.064550   0.195655  0.3299  0.74153
lag(log_VAP, 2)  -0.013744   0.058330 -0.2356  0.81378
lag(log_WAG, 2)  -0.030326   0.065098 -0.4658  0.64143
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    23.177
Residual Sum of Squares: 23.03
R-Squared:      0.0063354
Adj. R-Squared: 0.0013321
F-statistic: 1.26623 on 5 and 993 DF, p-value: 0.27626

Bootstrap p-value [Δlog_HERD_{t-2}] (country-cluster, B=9999): 0.531
```

Figure 8: First-Differences with Lagged Independent Variables (Lag 3)

```
Oneway (individual) effect First-Difference Model

Call:
plm(formula = log_BERD ~ lag(log_HERD, 3) + lag(log_GDP, 3) +
    lag(log_NOE, 3) + lag(log_VAP, 3) + lag(log_WAG, 3), data = pdata_reg,
    model = "fd")

Balanced Panel: n = 37, T = 27, N = 999
Observations used in estimation: 962

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-1.5824068 -0.0614824 -0.0084219  0.0407736  1.5835223

Coefficients:
                  Estimate Std. Error t-value Pr(>|t|)
(Intercept)      0.0646672  0.0079342  8.1504 1.13e-15 ***
lag(log_HERD, 3) 0.0386361  0.0275851  1.4006   0.1617
lag(log_GDP, 3)  0.0019508  0.1283023  0.0152   0.9879
lag(log_NOE, 3)  0.0618185  0.1939422  0.3187   0.7500
lag(log_VAP, 3)  0.0078077  0.0578749  0.1349   0.8927
lag(log_WAG, 3)  0.0736343  0.0644286  1.1429   0.2534
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    21.834
Residual Sum of Squares: 21.709
R-Squared:      0.0057548
Adj. R-Squared: 0.00055477
F-statistic: 1.10669 on 5 and 956 DF, p-value: 0.35509

Bootstrap p-value [Δlog_HERD_{t-3}] (country-cluster, B=9,999):  0.996
```

Figure 9: Two-Way FE vs First Differences (1–3-year lags)

Two-Way FE (lag 1) vs First Differences (k = 1-3 year lags)

	Dependent variable:			
	log(BERD)			
	TWFE k=1	FD k=1	FD k=2	FD k=3
	(1)	(2)	(3)	(4)
lag(log_HERD, 1)	0.3240	-0.0047		
	(0.2058)	(0.0349)		
lag(log_GDP, 1)	0.4886	0.2067		
	(0.4252)	(0.1684)		
lag(log_NOE, 1)	-0.8090	0.0457		
	(0.8451)	(0.2130)		
lag(log_VAP, 1)	-0.1801	-0.0137		
	(0.1806)	(0.0354)		
lag(log_WAG, 1)	0.2406	-0.0240		
	(0.2179)	(0.0431)		
lag(log_HERD, 2)			0.0599	
			(0.0452)	
lag(log_GDP, 2)			-0.1560**	
			(0.0741)	
lag(log_NOE, 2)			0.0645	
			(0.2079)	
lag(log_VAP, 2)			-0.0137	
			(0.0439)	
lag(log_WAG, 2)			-0.0303	
			(0.0337)	
lag(log_HERD, 3)				0.0386
				(0.0387)
lag(log_GDP, 3)				0.0020
				(0.1507)
lag(log_NOE, 3)				0.0618
				(0.2709)
lag(log_VAP, 3)				0.0078
				(0.0494)
lag(log_WAG, 3)				0.0736
				(0.0886)
Constant		0.0590***	0.0731***	0.0647***
		(0.0132)	(0.0065)	(0.0064)
Bootstrap p-value (HERD term)	0.975	0.743	0.531	0.996
Observations	1,073	1,036	999	962
R2	0.1773	0.0034	0.0063	0.0058
Adjusted R2	0.1207	-0.0014	0.0013	0.0006
F Statistic	43.2219*** (df = 5; 1003)	0.7100 (df = 5; 1030)	1.2662 (df = 5; 993)	1.1067 (df = 5; 956)
Note:				*p<0.1; **p<0.05; ***p<0.01
	SEs are country-clustered (HC1). Row shows wild/cluster bootstrap p-values for the HERD coefficient in each column.			

Figure 10: Two-Way FE: With Country-Specific Linear Trends

```
=== Two-Way FE: With Country Specific Linear Trends  ===

                   Estimate Std. Error     t value   Pr(>|t|)
lag(log_HERD, 1)  0.18696456  0.1233361  1.51589440 0.12987286
lag(log_GDP, 1)   0.86914642  0.4384694  1.98222801 0.04773645
lag(log_NOE, 1)   0.01074834  0.5471004  0.01964601 0.98432981
lag(log_VAP, 1)  -0.07006377  0.2046813 -0.34230660 0.73219456
lag(log_WAG, 1)  -0.01281634  0.1790694 -0.07157194 0.94295737

Bootstrap p-value for lag(log_HERD, 1) (country-cluster, B = 9,999): 0.989
```

Figure 11: Alternative Lag Specifications

Alternative Lag Specifications

	Dependent variable:		
		log_BERD	
	Single Lag	Distributed	Moving Avg
	(1)	(2)	(3)
log_HERD		0.1951***	
		(0.0674)	
lag(log_HERD, 1)	0.3240***	0.1564**	
	(0.0320)	(0.0660)	
log_HERD_ma3			0.3350***
			(0.0326)
lag(log_GDP, 1)	0.4886***	0.4663***	0.4794***
	(0.1197)	(0.1196)	(0.1197)
lag(log_NOE, 1)	-0.8090***	-0.8255***	-0.8763***
	(0.1921)	(0.1914)	(0.1907)
lag(log_VAP, 1)	-0.1801**	-0.1715**	-0.1722**
	(0.0875)	(0.0872)	(0.0874)
lag(log_WAG, 1)	0.2406***	0.2354***	0.2445***
	(0.0732)	(0.0730)	(0.0731)
Observations	1,073	1,073	1,073
R2	0.1773	0.1841	0.1795
Adjusted R2	0.1207	0.1271	0.1231
F Statistic	43.2219*** (df = 5; 1003)	37.6806*** (df = 6; 1002)	43.8930*** (df = 5; 1003)
Note:			*p<0.1; **p<0.05; ***p<0.01

```
Bootstrap p-values (country-cluster, B=9,999):
  Single Lag – lag(log_HERD, 1): 0.975
  Distributed – log_HERD: 0.966 | log_HERD_lag1: NA
  Moving Avg (MA3) – log_HERD_ma3: 0.995
```

A.4.3 Extensions to the Baseline Model

Figure 12: Cross-Country Spillover Model

Cross-Country Spillovers (TWFE)

	Dependent variable:
	log(BERD)
lag(log_HERD, 1)	0.3048***
	(0.0330)
lag_avg_HERD_other	-4.3642***
	(1.6763)
lag_log_GDP	0.4434***
	(0.1208)
lag_log_NOE	-0.8285***
	(0.2095)
lag_log_VAP	-0.1850**
	(0.0941)
lag_log_WAG	0.2533***
	(0.0801)
Observations	1,073
R2	0.1802
Adjusted R2	0.1230
F Statistic	36.7165*** (df = 6; 1002)
Note:	*p<0.1; **p<0.05; ***p<0.01

Bootstrap p-values (country-cluster, B = 9,999):
lag_log_HERD_1 (domestic HERD_{t-1}) : 0.955
lag_avg_HERD_other (foreign average) : 0.885

Figure 13: High vs Low R&D Intensity Countries

High vs Low HERD Intensity Countries (All Variables Lagged)

	Dependent variable:	
	log_BERD	
	High Intensity	Low Intensity
	(1)	(2)
lag(log_HERD, 1)	0.2260***	-0.0791
	(0.0667)	(0.0491)
lag(log_GDP, 1)	0.6561***	0.6738***
	(0.1656)	(0.1877)
lag(log_NOE, 1)	-0.1660	0.1519
	(0.2319)	(0.2849)
lag(log_VAP, 1)	0.0097	-0.0339
	(0.0886)	(0.1317)
lag(log_WAG, 1)	-0.2242***	0.3954***
	(0.0694)	(0.1152)
Cluster-bootstrap p (HERD lag 1)	0.973	0.952
Observations	515	512
R2	0.1165	0.0806
Adjusted R2	-0.0003	-0.0371
F Statistic	11.9725*** (df = 5; 454)	7.9465*** (df = 5; 453)
Note:		*p<0.1; **p<0.05; ***p<0.01
		p-values are country-cluster (pairs) bootstrap with B = 9,999; TWFE included in each draw.

A.4.4 Baseline Model

Figure 14: Model 1 — Two-Way FE: Contemporaneous HERD + Lag-1 Controls

```
Model 1 -Two-Way FE: Contemporaneous HERD + Lag-1 Controls
============================================
                    Dependent variable:
                ---------------------------
                         log(BERD)
--------------------------------------------
log_HERD                 0.3350***
                         (0.0326)

lag(log_GDP, 1)          0.4794***
                         (0.1197)

lag(log_NOE, 1)         -0.8763***
                         (0.1907)

lag(log_VAP, 1)          -0.1722**
                         (0.0874)

lag(log_WAG, 1)          0.2445***
                         (0.0731)

--------------------------------------------
Observations               1,073
R2                        0.1795
Adjusted R2               0.1231
F Statistic      43.8930*** (df = 5; 1003)
============================================
Note:            *p<0.1; **p<0.05; ***p<0.01

Bootstrap p-value [log_HERD] (country-cluster, B=9,999): 0.975
```

Figure 15: Model 2 — Two-Way FE: Lag-1 HERD and Controls

```
Model 2 -Two-Way FE: 1-year lag for all variables
============================================
                    Dependent variable:
                 ---------------------------
                         log(BERD)
--------------------------------------------
lag(log_HERD, 1)         0.3240***
                         (0.0320)

lag(log_GDP, 1)          0.4886***
                         (0.1197)

lag(log_NOE, 1)         -0.8090***
                         (0.1921)

lag(log_VAP, 1)          -0.1801**
                         (0.0875)

lag(log_WAG, 1)          0.2406***
                         (0.0732)

--------------------------------------------
Observations               1,073
R2                        0.1773
Adjusted R2               0.1207
F Statistic      43.2219*** (df = 5; 1003)
============================================
Note:            *p<0.1; **p<0.05; ***p<0.01

Bootstrap p-value [lag(log_HERD), 1] (country-cluster, B=9,999): 0.975
```

Figure 16: Model 3 — Two-Way FE: Lag-2 HERD and Controls

```
Model 3 - Two-Way FE: 2-year lag for all variables
============================================
                     Dependent variable:
                 ---------------------------
                          log(BERD)
--------------------------------------------
lag(log_HERD, 2)          0.2776***
                          (0.0318)

lag(log_GDP, 2)           0.5553***
                          (0.1221)

lag(log_NOE, 2)          -0.8138***
                          (0.1872)

lag(log_VAP, 2)          -0.2736***
                          (0.0858)

lag(log_WAG, 2)           0.2855***
                          (0.0714)

--------------------------------------------
Observations                1,036
R2                          0.1664
Adjusted R2                 0.1078
F Statistic        38.6142*** (df = 5; 967)
============================================
Note:            *p<0.1; **p<0.05; ***p<0.01

Bootstrap p-value [lag(log_HERD), 2] (country-cluster, B=9,999): 0.975
```

Figure 17: Model 4 — Two-Way FE: Lag-3 HERD and Controls

```
Model 4 - Two-Way FE: 3-year lag for all variables
============================================
                     Dependent variable:
                 ---------------------------
                          log(BERD)
--------------------------------------------
lag(log_HERD, 3)          0.2242***
                          (0.0316)

lag(log_GDP, 3)           0.6353***
                          (0.1269)

lag(log_NOE, 3)          -0.8753***
                          (0.1819)

lag(log_VAP, 3)          -0.3620***
                          (0.0842)

lag(log_WAG, 3)           0.3315***
                          (0.0693)

--------------------------------------------
Observations                  999
R2                          0.1590
Adjusted R2                 0.0984
F Statistic        35.1921*** (df = 5; 931)
============================================
Note:            *p<0.1; **p<0.05; ***p<0.01

Bootstrap p-value [lag(log_HERD), 3] (country-cluster, B=9,999): 0.968
```

Figure 18: Model 5 — Two-Way FE: All HERD Lags + Lag-1 Controls

```
Model 5 - Two-Way FE: All Lags Together
===========================================
                 Dependent variable:
              ----------------------------
                      log(BERD)
-------------------------------------------
log_HERD                0.2075***
                        (0.0654)

lag(log_HERD, 1)         -0.0268
                        (0.0876)

lag(log_HERD, 2)         -0.0091
                        (0.0871)

lag(log_HERD, 3)        0.1535**
                        (0.0630)

lag(log_GDP, 1)         0.5694***
                        (0.1202)

lag(log_NOE, 1)        -0.8070***
                        (0.2157)

lag(log_VAP, 1)        -0.3599***
                        (0.0955)

lag(log_WAG, 1)         0.3272***
                        (0.0817)

-------------------------------------------
Observations               999
R2                        0.1691
Adjusted R2               0.1064
F Statistic       23.6095*** (df = 8; 928)
===========================================
Note:           *p<0.1; **p<0.05; ***p<0.01

Bootstrap p-values for HERD terms (country-cluster, B=9,999):
  log_HERD (t)        : 0.208
  lag(log_HERD, 1)    : 0.942
  lag(log_HERD, 2)    : 0.882
  lag(log_HERD, 3)    : 0.594
```

Table 13: Two-Way Fixed Effects: HERD Spillovers to BERD (Comprehensive Lags)

Variable	Contemp. (m1)	Lag 1 (m2)	Lag 2 (m3)	Lag 3 (m4)	All Lags (m5)
log(HERD)_t	0.3350***				0.2075***
	(0.0326)				(0.0654)
lag(log(HERD), 1)		0.3240***			–0.0268
		(0.0320)			(0.0876)
lag(log(HERD), 2)			0.2776***		0.5694***
			(0.0318)		(0.1202)
lag(log(HERD), 3)				0.2242***	–0.8070***
				(0.0316)	(0.2157)
lag(log(GDP), 1)	0.4794**	0.4889***	0.5554***	0.6353***	–0.3599***
lag(log(NOE), 1)	–0.8763***	–0.8090***	–0.8138***	–0.8753***	0.3272***
lag(log(VAP), 1)	–0.1722**	–0.1801**	0.2776***	–0.3620***	–0.0091
lag(log(WAG), 1)	0.2445***	0.2406***	0.5553***	0.3315***	…
Observations	1,073	1,073	1,036	999	999
R^2	0.1795	0.1773	0.1664	0.1590	0.1691
Adj. R^2	0.1231	0.1207	0.1078	0.0984	0.1064

A.4.5 IV Estimation

Figure 19: IV (2SLS) Estimation Results with Lagged Variables

```
=== FE-IV (2SLS): coefficients (clustered by country), FE omitted ===
               Estimate Std. Error t value Pr(>|t|)
(Intercept)     14.5551     7.8829  1.8464   0.0651
log_HERD_lag1   -1.9899     1.5577 -1.2775   0.2017
log_GDP_lag1     2.2621     1.2443  1.8180   0.0693
log_NOE_lag1    -3.3553     1.7580 -1.9086   0.0566
log_VAP_lag1    -0.5056     0.3596 -1.4058   0.1601
log_WAG_lag1     1.0207     0.5881  1.7356   0.0829

=== IV diagnostics ===
                  df1  df2 statistic      p-value
Weak instruments    1 1039   2.73539 0.0984496171
Wu-Hausman          1 1038  14.50590 0.0001479164
Sargan              0   NA        NA           NA
```

Figure 20: Comparison: OLS vs IV (2SLS)

Comparison: OLS vs IV (2SLS) with FE (FE hidden)

	Dependent variable:	
	log(BERD)	
	OLS	instrumental variable
	OLS	IV (2SLS)
	(1)	(2)
log_HERD_lag1	0.9372***	-1.9899
	(0.0376)	(1.5577)
log_GDP_lag1	0.2234***	2.2621*
	(0.0549)	(1.2443)
log_NOE_lag1	-0.0597	-3.3553*
	(0.0447)	(1.7580)
log_VAP_lag1	-0.0470**	-0.5056
	(0.0183)	(0.3596)
log_WAG_lag1	0.1089***	1.0207*
	(0.0209)	(0.5881)
Observations	1,110	1,110
R2	0.8655	0.8422
Adjusted R2	0.8649	0.8316
Residual Std. Error	0.7858 (df = 1104)	0.8772 (df = 1039)
F Statistic	1,420.4360*** (df = 5; 1104)	
Note:		*p<0.1; **p<0.05; ***p<0.01

A.4.6 Generalized Method of Moments Estimation

Figure 21: System GMM Results with Lagged Structure

```
Twoways effects One-step model System GMM

Call:
pgmm(formula = log_BERD ~ lag(log_BERD, 1) + lag(log_HERD, 1) +
    lag(log_GDP, 1) + lag(log_NOE, 1) | lag(log_BERD, 2:3) +
    lag(log_HERD, 2:3), data = pdata_gmm, effect = "twoways",
    model = "onestep", collapse = TRUE, transformation = "ld")

Balanced Panel: n = 37, T = 30, N = 1110

Number of Observations Used: 2109
Residuals:
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-1.43509 -0.08363 -0.01345  0.00000  0.06325  1.81715

Coefficients:
                  Estimate Std. Error z-value Pr(>|z|)
lag(log_BERD, 1)  1.090713   0.097310 11.2087   <2e-16 ***
lag(log_HERD, 1)  0.077043   0.063043  1.2221   0.2217
lag(log_GDP, 1)  -0.179454   0.113954 -1.5748   0.1153
lag(log_NOE, 1)  -0.013676   0.078440 -0.1743   0.8616
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Sargan test: chisq(6) = 34.77573 (p-value = 4.7628e-06)
Autocorrelation test (1): normal = -3.289295 (p-value = 0.0010044)
Autocorrelation test (2): normal = -0.8524583 (p-value = 0.39396)
Wald test for coefficients: chisq(4) = 18652.22 (p-value = < 2.22e-16)
Wald test for time dummies: chisq(28) = 638.7403 (p-value = < 2.22e-16)
```

Figure 22: Arellano-Bond GMM Results

```
Oneway (individual) effect One-step model Difference GMM

Call:
pgmm(formula = log_BERD ~ lag(log_BERD, 1) + lag(log_HERD, 1) +
    lag(log_GDP, 1) + lag(log_NOE, 1) | lag(log_BERD, 2:3), data = pdata_gmm,
    effect = "individual", model = "onestep", collapse = TRUE,
    transformation = "d")

Balanced Panel: n = 37, T = 30, N = 1110

Number of Observations Used: 1036
Residuals:
      Min.    1st Qu.     Median       Mean    3rd Qu.       Max.
-2.4254085 -0.0731583  0.0030157 -0.0003913  0.0758426  2.8054111

Coefficients:
                 Estimate Std. Error z-value  Pr(>|z|)
lag(log_BERD, 1)  1.83136    0.50363  3.6364 0.0002765 ***
lag(log_HERD, 1) -0.26473    0.13482 -1.9635 0.0495875 *
lag(log_GDP, 1)  -0.87108    0.67069 -1.2988 0.1940235
lag(log_NOE, 1)   0.19299    0.38813  0.4972 0.6190353
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Sargan test: chisq(1) = 0.5153953 (p-value = 0.47281)
Autocorrelation test (1): normal = -2.253864 (p-value = 0.024205)
Autocorrelation test (2): normal = -0.814854 (p-value = 0.41516)
Wald test for coefficients: chisq(4) = 485.9631 (p-value = < 2.22e-16)
```

A.4.7 Total Factor Productivity Analysis

Figure 23: TFP Analysis with Lagged HERD

```
Twoways effects Within Model

Call:
plm(formula = TFP ~ lag(log_HERD, 1) + lag(log_BERD, 1) + lag(log_GDP,
    1) + lag(log_WAG, 1), data = pdata_tfp, effect = "twoways",
    model = "within")

Balanced Panel: n = 37, T = 29, N = 1073

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-4.9746e-01 -3.8967e-02 -6.1641e-05  3.4793e-02  7.4066e-01

Coefficients:
                   Estimate Std. Error t-value  Pr(>|t|)
lag(log_HERD, 1) -0.0148371  0.0088157 -1.6830   0.09268 .
lag(log_BERD, 1)  0.0131956  0.0081167  1.6257   0.10432
lag(log_GDP, 1)   0.2242800  0.0288922  7.7627 2.042e-14 ***
lag(log_WAG, 1)   0.2444329  0.0161207 15.1627 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    12.147
Residual Sum of Squares: 8.2344
R-Squared:      0.32211
Adj. R-Squared: 0.2762
F-statistic: 119.266 on 4 and 1004 DF, p-value: < 2.22e-16

Bootstrap p-value [lag(log_HERD), 1] (country-cluster, B=9,999): 0.881
```

B Error Correction Framework

B.1 Long-run (cointegrating) relation in levels

Let $y_{i,t} \equiv \ln(\text{BERD})_{i,t}$ and

$$x_{i,t} \equiv \begin{bmatrix} \ln(HERD)_{i,t} \\ \ln(GDP)_{i,t} \\ \ln(NOE)_{i,t} \\ \ln(VAP)_{i,t} \\ \ln(WAG)_{i,t} \end{bmatrix}.$$

We estimate the within-country, within-year levels specification:

$$y_{i,t} = \beta' x_{i,t} + \alpha_i + \delta_t + u_{i,t} \qquad \text{(B1)}$$

where α_i and δ_t are country and year fixed effects and $u_{i,t}$ the residuals. The estimated residuals:

$$\widehat{ECT_{i,t}} \equiv \widehat{u_{i,t}}$$

are the error-correction term (the deviation of $y_{i,t}$ from its long-run path implied by $x_{i,t}$ after absorbing FE). The long-run elasticity of BERD with respect to HERD is the HERD element of β, denoted β_{HERD}.

B.2 Short-run dynamics (Error-Correction Model)

Define annual first differences $\Delta z_{it} \equiv z_{it} - z_{i,t-1}$. The short-run adjustment is modeled as:

$$\Delta y_{i,t} = \gamma' \Delta x_{i,t} + \lambda \widehat{ECT_{i,t-1}} + \tau_t + \varepsilon_{i,t} \qquad \text{(B2)}$$

with year fixed effects τ_t to absorb global shocks. Here γ collects short-run elasticities (impact effects of annual changes in the covariates) and $\lambda < 0$ is the speed of adjustment toward the long-run relation in (B1). An adjustment speed $s \equiv -\lambda$ implies a half-life:

$$HL = \frac{\ln(0.5)}{\ln(1-s)}$$

Equation (B1) is estimated by TWFE in logs; $\widehat{ECT}_{i,t}$ is the resulting within-residual. Equation (B2) is estimated by OLS on annual differences with year dummies, using country-clustered standard errors. Variables are aligned so that $\widehat{ECT}_{i,t-1}$ is the lag of the residual from (B1), and $\Delta x_{i,t}$ are adjacent-year differences.

Figure 24: Error-Correction Model for $\Delta\ln\,(BERD)$

```
ECM: Δlog(BERD) with Year FE (clustered by country)
==============================================
                    Dependent variable:
                --------------------------
                        Δlog(BERD)
----------------------------------------------
D_log_HERD               0.1568**
                        (0.0687)

D_log_GDP                0.4288***
                        (0.1419)

D_log_NOE                -0.1439
                        (0.2177)

D_log_VAP                 0.0559
                        (0.0356)

D_log_WAG                -0.1107
                        (0.0755)

ECT_lag1                -0.1049***
                        (0.0254)

Constant                 0.0301**
                        (0.0153)

----------------------------------------------
Observations               1,073
R2                        0.1610
Adjusted R2               0.1335
Residual Std. Error    0.1393 (df = 1038)
F Statistic         5.8566*** (df = 34; 1038)
==============================================
Note:              *p<0.1; **p<0.05; ***p<0.01

Bootstrap p-value [D_log_HERD] (country-cluster pairs, B = 9,999): 0.993
```

From our run of (B2):

$$\hat{\gamma}_{\mathrm{HERD}} \approx 0.157\ (\mathrm{SE}\ 0.069,\ p = 0.993), \hat{\lambda} \approx -0.104\ (\mathrm{SE}\ 0.025,\ p < 0.001).$$

Thus, a 10% increase in HERD is associated with roughly a 1.6% increase in BERD within a year (modest short-run effect), while deviations from the long-run BERD–HERD relation close by about 10% per year. The implied half-life is

$$\mathrm{HL} \approx \frac{\ln(0.5)}{\ln(1-0.104)} \approx 6.3 \text{ years,}$$

convergence toward the long-run path is gradual—exactly the cointegration pattern that reconciles our FE levels results (medium-run association) with the weaker FD/short-run evidence.

C No Interpolation Sample Outputs

C.1 Robustness Checks

Figure 25: First-Differences with Lagged Independent Variables (Lag 1)

```
First-Differences (no interpolation) — horizon 1:
Oneway (individual) effect First-Difference Model

Call:
plm(formula = log_BERD ~ log_HERD_lag1 + log_GDP_lag1 + log_NOE_lag1 +
    log_VAP_lag1 + log_WAG_lag1, data = pdata_noi, model = "fd")

Unbalanced Panel: n = 29, T = 3-23, N = 554
Observations used in estimation: 525

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-1.002994 -0.058875 -0.014566  0.042310  1.691426

Coefficients:
               Estimate Std. Error t-value  Pr(>|t|)
(Intercept)    0.070274   0.012592  5.5810 3.859e-08 ***
log_HERD_lag1 -0.145303   0.056057 -2.5920   0.00981 **
log_GDP_lag1   0.670316   0.343848  1.9495   0.05178 .
log_NOE_lag1  -0.268293   0.419519 -0.6395   0.52276
log_VAP_lag1  -0.597908   0.380524 -1.5713   0.11673
log_WAG_lag1   0.385001   0.294245  1.3084   0.19130
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    14.742
Residual Sum of Squares: 14.483
R-Squared:      0.017526
Adj. R-Squared: 0.0080609
F-statistic: 1.85165 on 5 and 519 DF, p-value: 0.10123
```

Figure 26: : First-Differences with Lagged Independent Variables (Lag 2)

```
First-Differences (no interpolation) — horizon 2:
Oneway (individual) effect First-Difference Model

Call:
plm(formula = log_BERD ~ log_HERD_lag2 + log_GDP_lag2 + log_NOE_lag2 +
    log_VAP_lag2 + log_WAG_lag2, data = pdata_noi, model = "fd")

Unbalanced Panel: n = 29, T = 3-23, N = 565
Observations used in estimation: 536

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-0.712714 -0.059845 -0.011870  0.040995  1.674938

Coefficients:
               Estimate Std. Error t-value Pr(>|t|)
(Intercept)    0.063271   0.011917  5.3095 1.62e-07 ***
log_HERD_lag2  0.039145   0.052784  0.7416  0.45866
log_GDP_lag2   0.291438   0.322905  0.9025  0.36718
log_NOE_lag2  -0.575814   0.389829 -1.4771  0.14024
log_VAP_lag2  -0.440976   0.359305 -1.2273  0.22025
log_WAG_lag2   0.547877   0.277203  1.9764  0.04862 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    13.597
Residual Sum of Squares: 13.433
R-Squared:      0.012046
Adj. R-Squared: 0.0027259
F-statistic: 1.29247 on 5 and 530 DF, p-value: 0.2656
```

Figure 27: : First-Differences with Lagged Independent Variables (Lag 3)

```
First-Differences (no interpolation) — horizon 3:
Oneway (individual) effect First-Difference Model

Call:
plm(formula = log_BERD ~ log_HERD_lag3 + log_GDP_lag3 + log_NOE_lag3 +
    log_VAP_lag3 + log_WAG_lag3, data = pdata_noi, model = "fd")

Unbalanced Panel: n = 29, T = 2-23, N = 560
Observations used in estimation: 531

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.7322606 -0.0563134 -0.0083946  0.0415542  1.6394132

Coefficients:
               Estimate Std. Error t-value  Pr(>|t|)
(Intercept)    0.060155   0.011529  5.2178 2.611e-07 ***
log_HERD_lag3  0.049461   0.050494  0.9795    0.3278
log_GDP_lag3  -0.201286   0.308290 -0.6529    0.5141
log_NOE_lag3  -0.240054   0.378857 -0.6336    0.5266
log_VAP_lag3   0.373210   0.339645  1.0988    0.2723
log_WAG_lag3   0.222684   0.269766  0.8255    0.4095
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    12.744
Residual Sum of Squares: 12.381
R-Squared:      0.028501
Adj. R-Squared: 0.019249
F-statistic: 3.08044 on 5 and 525 DF, p-value: 0.0094477
```

Figure 28: Two-Way FE vs First Differences (1–3-year lags)

Two-Way FE vs First Differences (1-3-year lags) – No-Interpolation Sample

	Dependent variable:			
	log(BERD)			
	FE k=1 (TWFE)	FD k=1	FD k=2	FD k=3
	(1)	(2)	(3)	(4)
log_HERD_lag1	-0.1546	-0.1453**		
	(0.1487)	(0.0592)		
log_GDP_lag1	2.0027*	0.6703**		
	(1.1216)	(0.3219)		
log_NOE_lag1	-1.1153	-0.2683		
	(0.9054)	(0.6894)		
log_VAP_lag1	-1.0297	-0.5979*		
	(1.0845)	(0.3392)		
log_WAG_lag1	0.8986	0.3850*		
	(0.7913)	(0.2066)		
log_HERD_lag2			0.0391	
			(0.0575)	
log_GDP_lag2			0.2914	
			(0.2999)	
log_NOE_lag2			-0.5758	
			(0.6787)	
log_VAP_lag2			-0.4410	
			(0.7288)	
log_WAG_lag2			0.5479	
			(0.7830)	
log_HERD_lag3				0.0495
				(0.0856)
log_GDP_lag3				-0.2013
				(0.3887)
log_NOE_lag3				-0.2401
				(0.7362)
log_VAP_lag3				0.3732
				(0.4555)
log_WAG_lag3				0.2227
				(0.5822)
Constant		0.0703***	0.0633***	0.0602***
		(0.0154)	(0.0089)	(0.0129)
Observations	554	525	536	531
R2	0.1775	0.0175	0.0120	0.0285
Adjusted R2	0.0866	0.0081	0.0027	0.0192
F Statistic	21.4922*** (df = 5; 498)	1.8516 (df = 5; 519)	1.2925 (df = 5; 530)	3.0804*** (df = 5; 525)
Note:				*p<0.1; **p<0.05; ***p<0.01

Figure 29: Two-Way FE: With Country Specific Linear Trends

=== Two-Way FE: With Country Specific Linear Trends ===

	Estimate	Std. Error	t value	Pr(>|t|)
log_HERD_lag1	0.2496666	0.1175857	2.12327271	0.03425290
log_GDP_lag1	1.6244259	0.6573987	2.47099045	0.01382753
log_NOE_lag1	0.8134708	0.9786946	0.83117939	0.40629435
log_VAP_lag1	-0.9187618	0.7771956	-1.18215006	0.23774389
log_WAG_lag1	-0.0105349	0.4527955	-0.02326635	0.98144769

Figure 30: Alternative Lag Specifications

Alternative Lag Specifications — No-Interpolation Sample

	Dependent variable:		
	log(BERD)		
	Single Lag	Distributed	Moving Avg (MA3)
	(1)	(2)	(3)
log_HERD		0.2104	
		(0.2044)	
log_HERD_lag1	-0.1546	-0.3173**	
	(0.1487)	(0.1291)	
log_HERD_ma3			-0.1294
			(0.1926)
log_GDP_lag1	2.0027*	1.9653*	1.9489*
	(1.1216)	(1.1164)	(1.0917)
log_NOE_lag1	-1.1153	-1.0790	-1.1012
	(0.9054)	(0.9017)	(0.8883)
log_VAP_lag1	-1.0297	-1.0110	-0.8035
	(1.0845)	(1.0843)	(1.0696)
log_WAG_lag1	0.8986	0.8819	0.7087
	(0.7913)	(0.7852)	(0.7984)
Observations	554	551	526
R2	0.1775	0.1852	0.1778
Adjusted R2	0.0866	0.0928	0.0835
F Statistic	21.4922*** (df = 5; 498)	18.7082*** (df = 6; 494)	20.3715*** (df = 5; 471)
Note:			*p<0.1; **p<0.05; ***p<0.01

C.2 Extensions to the Baseline Model

Figure 31: Cross-Country Spillover Model

Cross-Country Spillovers (No-Interpolation Sample)

	Dependent variable: log(BERD)
log_HERD_lag1	-0.0924
	(0.1726)
log_GDP_lag1	1.1245
	(1.0077)
log_NOE_lag1	-0.8770
	(0.8830)
log_VAP_lag1	-0.2662
	(0.9586)
log_WAG_lag1	0.4694
	(0.7302)
Observations	381
R2	0.1441
Adjusted R2	0.0204
F Statistic	11.1789*** (df = 5; 332)
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 32: High vs Low R&D Intensity Countries

High vs Low HERD Intensity (No-Interpolation, All Vars Lagged 1)

	Dependent variable: log(BERD)	
	High Intensity	Low Intensity
	(1)	(2)
log_HERD_lag1	0.2458	-0.3718***
	(0.1513)	(0.0944)
log_GDP_lag1	0.4963	2.2717*
	(0.4668)	(1.3366)
log_NOE_lag1	-1.3387**	-0.1941
	(0.6325)	(0.8838)
log_VAP_lag1	0.7359	-2.2684
	(0.5815)	(1.4137)
log_WAG_lag1	-0.0338	1.7030*
	(0.5016)	(0.8972)
Observations	276	275
R2	0.3028	0.1475
Adjusted R2	0.1516	-0.0156
F Statistic	19.6292*** (df = 5; 226)	7.9576*** (df = 5; 230)
Note:		*p<0.1; **p<0.05; ***p<0.01

C.3 Baseline Model

Figure 33: Two-Way FE - Contemporaneous HERD + Lag-1 Controls

Two-Way FE: Contemporaneous HERD + Lag-1 Controls

	Dependent variable:
	log(BERD)
log_HERD	-0.1147**
	(0.0507)
lag(log_GDP, 1)	1.9540***
	(0.3570)
lag(log_NOE, 1)	-1.3522***
	(0.2410)
lag(log_VAP, 1)	-1.0328**
	(0.4059)
lag(log_WAG, 1)	0.9427***
	(0.2998)
Observations	569
R2	0.1958
Adjusted R2	0.1095
F Statistic	24.9749*** (df = 5; 513)
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 34: Two-Way FE - Lag-1 HERD and Controls

Two-Way FE: Lag-1 HERD and Controls

	Dependent variable:
	log(BERD)
lag(log_HERD, 1)	-0.1546***
	(0.0558)
lag(log_GDP, 1)	2.0027***
	(0.3632)
lag(log_NOE, 1)	-1.1153***
	(0.2446)
lag(log_VAP, 1)	-1.0297**
	(0.4071)
lag(log_WAG, 1)	0.8986***
	(0.3010)
Observations	554
R2	0.1775
Adjusted R2	0.0866
F Statistic	21.4922*** (df = 5; 498)
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 35: Two-Way FE - Lag-2 HERD and Controls

Two-Way FE: Lag-2 HERD and Controls

	Dependent variable:
	log(BERD)
lag(log_HERD, 2)	-0.1375***
	(0.0508)
lag(log_GDP, 2)	1.6561***
	(0.3511)
lag(log_NOE, 2)	-1.0581***
	(0.2353)
lag(log_VAP, 2)	-0.6220
	(0.3958)
lag(log_WAG, 2)	0.6772**
	(0.2919)
Observations	565
R2	0.1777
Adjusted R2	0.0889
F Statistic	21.9999*** (df = 5; 509)
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 36: Two-Way FE - Lag-3 HERD and Controls

Two-Way FE: Lag-3 HERD and Controls

	Dependent variable:
	log(BERD)
lag(log_HERD, 3)	-0.1417***
	(0.0428)
lag(log_GDP, 3)	1.1038***
	(0.3174)
lag(log_NOE, 3)	-0.8979***
	(0.2103)
lag(log_VAP, 3)	0.2903
	(0.3558)
lag(log_WAG, 3)	0.0635
	(0.2647)
Observations	560
R2	0.2032
Adjusted R2	0.1163
F Statistic	25.7077*** (df = 5; 504)
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 37: Two-Way FE - All Lags Together

```
Two-Way FE: All Lags Together
===========================================
                    Dependent variable:
                ---------------------------
                         log(BERD)
-------------------------------------------
log_HERD                  0.2152*
                         (0.1156)

lag(log_HERD, 1)         -0.2540*
                         (0.1477)

lag(log_HERD, 2)          0.0014
                         (0.1496)

lag(log_HERD, 3)          -0.0306
                         (0.1065)

lag(log_GDP, 1)          1.4828***
                         (0.3975)

lag(log_NOE, 1)         -0.9554***
                         (0.2503)

lag(log_VAP, 1)           -0.2866
                         (0.4344)

lag(log_WAG, 1)           0.4409
                         (0.3001)

-------------------------------------------
Observations                501
R2                        0.1991
Adjusted R2               0.0981
F Statistic       13.7971*** (df = 8; 444)
===========================================
Note:           *p<0.1; **p<0.05; ***p<0.01
```

C.4 IV Estimation

Figure 38: IV (2SLS) Estimation Results with Lagged Variables

```
=== IV (2SLS) Estimation Results with Lagged Variables ===

t test of coefficients:

               Estimate Std. Error t value  Pr(>|t|)
(Intercept)   -8.115976   2.665288 -3.0451 0.0024526 **
log_HERD_lag1 -0.064492   0.379495 -0.1699 0.8651258
log_GDP_lag1   2.016356   0.600974  3.3551 0.0008553 ***
log_NOE_lag1  -0.961645   0.272408 -3.5302 0.0004548 ***
log_VAP_lag1  -2.529364   0.636455 -3.9741 8.135e-05 ***
log_WAG_lag1   2.627866   0.618286  4.2502 2.561e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


--- IV Diagnostics (AER::ivreg) ---
                 df1 df2 statistic      p-value
Weak instruments   3 484 52.006708 3.758317e-29
Wu-Hausman         1 485 11.405988 7.909543e-04
Sargan             2  NA  5.609176 6.053172e-02
```

C.5 Generalized Method of Moments Estimation

Figure 39: System GMM

```
=== System GMM Results with Lagged Structure ===
Oneway (individual) effect One-step model System GMM

Call:
pgmm(formula = log_BERD ~ lag(log_BERD, 1) + lag(log_HERD, 1) +
    lag(log_GDP, 1) + lag(log_NOE, 1) + lag(log_VAP, 1) + lag(log_WAG,
    1) | lag(log_BERD, 2:3) + lag(log_HERD, 2:3), data = pdata_gmm,
    effect = "individual", model = "onestep", collapse = TRUE,
    transformation = "ld", time.dummies = TRUE)

Unbalanced Panel: n = 27, T = 11-21, N = 492

Number of Observations Used: 900
Residuals:
      Min.    1st Qu.     Median       Mean    3rd Qu.       Max.
-0.9661907 -0.0505475  0.0000000 -0.0006665  0.0560184  1.3213439

Coefficients:
                  Estimate Std. Error z-value  Pr(>|z|)
lag(log_BERD, 1)  0.788964   0.145358  5.4277 5.708e-08 ***
lag(log_HERD, 1)  0.144885   0.115109  1.2587    0.2081
lag(log_GDP, 1)   0.074008   0.071091  1.0410    0.2979
lag(log_NOE, 1)  -0.025064   0.050280 -0.4985    0.6181
lag(log_VAP, 1)  -0.386316   0.406993 -0.9492    0.3425
lag(log_WAG, 1)   0.414033   0.423809  0.9769    0.3286
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Sargan test: chisq(8) = 18.59197 (p-value = 0.017201)
Autocorrelation test (1): normal = -1.652569 (p-value = 0.098419)
Autocorrelation test (2): normal = -0.2179331 (p-value = 0.82748)
Wald test for coefficients: chisq(6) = 312295.2 (p-value = < 2.22e-16)
```

Figure 40: Arellano-Bond GMM

```
=== Arellano-Bond GMM Results ===
Oneway (individual) effect One-step model Difference GMM

Call:
pgmm(formula = log_BERD ~ lag(log_BERD, 1) + lag(log_HERD, 1) +
    lag(log_GDP, 1) + lag(log_NOE, 1) | lag(log_BERD, 2:3) +
    lag(log_HERD, 2:3) + lag(log_GDP, 2:3) + lag(log_NOE, 2:3),
    data = pdata_gmm, effect = "individual", model = "onestep",
    collapse = TRUE, transformation = "d", time.dummies = TRUE)

Unbalanced Panel: n = 27, T = 11-21, N = 492

Number of Observations Used: 436
Residuals:
      Min.    1st Qu.     Median       Mean    3rd Qu.       Max.
-1.1053623 -0.0508178  0.0000000  0.0007091  0.0510150  1.4268594

Coefficients:
                   Estimate Std. Error z-value Pr(>|z|)
lag(log_BERD, 1)  0.9750784  0.7885783  1.2365   0.2163
lag(log_HERD, 1)  0.0050037  0.6105363  0.0082   0.9935
lag(log_GDP, 1)  -0.4006408  2.7906232 -0.1436   0.8858
lag(log_NOE, 1)   2.2132392  3.9559647  0.5595   0.5758

Sargan test: chisq(4) = 2.132712 (p-value = 0.71137)
Autocorrelation test (1): normal = -0.9397501 (p-value = 0.34735)
Autocorrelation test (2): normal = -0.3353588 (p-value = 0.73735)
Wald test for coefficients: chisq(4) = 851.3459 (p-value = < 2.22e-16)
```

C.6 Total Factor Productivity Analysis

Figure 41: TFP Analysis with Lagged HERD

TFP Regression (No-Interpolation, TWFE; all regressors lagged 1y)

	Dependent variable:
	TFP
log_HERD_lag1	-0.0249
	(0.0250)
log_BERD_lag1	0.0239
	(0.0239)
log_GDP_lag1	0.2090**
	(0.0872)
log_WAG_lag1	0.3667***
	(0.0506)
Observations	528
R2	0.7072
Adjusted R2	0.6745
F Statistic	286.2037*** (df = 4; 474)
Note:	*p<0.1; **p<0.05; ***p<0.01