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Causality in Economics: Policy Evaluation and Natural Experimentation

Causalidade em Economia: O Saber de Experiências Feito[1]

Paulino Teixeira

ABSTRACT
We discuss the importance of causality in economics, particularly in the area of labor economics. Causation is at the root of the analysis applied to facts, that is, as a means of explaining events. It is therefore intimately linked to decision-making or the making of decisions. As a true thought experiment, causation is illustrated in the context of natural experiments, that is, through proper construction of counterfactuals applied to minimum wage issues, trade union wage premium, management practices and firm performance, and, more broadly, to the role of institutions in economic growth.
Keywords: Causality, policy evaluation, minimum wage effects, union premium, management practices, institutions and economic growth

JEL Classification: C81; C93; D22; D7; J23; J31; L25; J51

[1] Oração de sapiência proferida na abertura solene do ano escolar da Universidade de Coimbra, no dia 1 de outubro de 2025.

Experimento hoje a “graça única” de proferir a oração de sapiência no antigo Paço Real e Sala do Trono. Cumpre-me dar continuidade às duas únicas lições aqui proferidas no âmbito da ciência económica, pelos professores Teixeira Ribeiro, em 1965, e João Sousa Andrade, em 2017. Não falarei sobre impostos, essa certeza tão certa quanto a morte, a que aludia o professor Teixeira Ribeiro; nem sobre o EURO, essa criação política mais do que económica (Feldstein, 2009).[2]

Creio que esta tradição de *oração de princípio no estudo* (ou *oração de abertura dos estudos*) se deve à iniciativa do então protetor da Universidade, o Infante D. Henrique. Ao Infante se deve a obrigação de uma intervenção inaugural por parte do lente de *Prima de Teologia* (Marcos, 2009, p. vi), em troca de uma verba perpétua retirada dos dízimos da Ilha da Madeira de que era donatário. Impendia então o dever de “fazer-se um discurso em louvor das ciências e de quem as professa” (p. vii), e que na tradição que se seguiria, ficaria a cargo de “pessoa grave e de talento” (p. xxix). Julgo que a primeira qualidade não me será estranha; da segunda direi apenas que sobre nós cabe aos outros falar!

Abordarei então um tema de economia. Desde há muito que a oração de sapiência se tornou obediente ao princípio da especialização e eu não vou fugir à regra.

Talvez deva começar por dizer que o ato de escrever *sobre* economia me é de alguma forma estranho ou contranatura. Parafraseando um conhecido matemático, G. Harold Hardy, *falar sobre* economia em vez de *fazer* economia é uma confissão de fraqueza (Hardy, 1967, p. 63). E só pode haver uma razão: *I'm over the age of sixty*!

Dizia o filósofo e escritor francês Paul Valéry que “só se pode chamar ciência ao conjunto de receitas que funcionam sempre. Tudo o resto é literatura”. Certamente pretendia dizer que uma mesma prescrição obriga ao mesmo resultado se todo o resto for constante.

Ocupar-me-ei nesta lição do nexo causal em economia, uma preocupação que remonta aos primórdios da ciência económica, como justamente ilustra o título do famoso tratado “Um Inquérito sobre a Natureza e as Causas da Riqueza das Nações” (Smith, 1776). “Feliz o que pode conhecer as causas das coisas”, afirmava Blaise Pascal, em frase creio que devida ao poeta latino Virgílio (Pascal, 2019, p. 65).[3]

A procura da causa é a procura da verdade, porque, precisamente, descobrir a causa de um fenómeno ou de um evento é explicá-lo. Na política não se ganham votos com a verdade; a verdade é para a ciência. Dizia também Robert Musil, na sua obra *O Homem sem Qualidades* (2008, p. 347), que um homem que busca a verdade se torna sábio; se der azo à subjetividade torna-se, talvez, escritor.

Economics pode ser vista à luz de variados ângulos (Hicks, 1980, viii). Como atração intelectual; ou seja, como um puro jogo (*a good game*), uma faceta não deslustrosa, porque há outros campos científicos onde o mesmo se pode aplicar: na matemática pura, por exemplo. Há depois uma parte da teoria económica que, preocupada com arranjos ideais, não está longe da ideologia. Ou aquela que relaciona os meios com os fins, frequentemente também de propósito ideológico, mas que, não obstante, pode ser conduzida realisticamente e com resultados, como na análise custo-benefício. Ou ainda a vertente de pendor sobretudo

[2] Para este autor, “the primary motivation for the creation of the euro was political, not economic;” e o argumento de que “one-market needs one money” é falso (Martin Feldstein, 2009).

[3] Felix qui potuit rerum cognoscere causas.

descritivo, de *ups and downs*, depreciativamente considerada como 'literatura de aeroporto' porque pouco intensa na utilização de caracteres gregos.

Mas também há aquela versão resumida na expressão *analysis applied to facts* (Hicks, p. ix), em que a teoria económica surge como meio de explicação, que diz não meramente o que acontece, mas por que aconteceu. É nesta aceção que emerge a causalidade em economia.

Nos seus próprios termos, a relação entre causa e efeito parece ser assunto para filósofos, e os economistas em geral dão-se por satisfeitos pelo facto de a discussão fundamental lhes ser alheia. Mas que não reste qualquer dúvida: a causalidade é central em economia – se não for por outra razão, porque há demasiada ambiguidade e erro, porventura muito para além do admissível.

Em economia não se pode dizer que o sol nascerá com toda a certeza amanhã de manhã, como 2+2 são 4, dizia John Hicks. Em economia não há destas certezas, o que na verdade, ou pelo menos em certa medida, como veremos adiante, é uma vantagem ou até um luxo. E também, diga-se, não há certezas em meteorologia ou em medicina, embora com diferentes graus de imponderabilidade.

Causa e efeito estão marcados no tempo. Contudo, a preocupação com a explicação dos eventos não obsta a que para o economista a preocupação central se situe no presente (Hicks, pp. 3-4). E nesta prioridade dada ao presente o economista distingue-se, creio, do historiador. O economista usa os factos do passado para construir generalizações que possam ser utilizadas *hoje*. Dito de outra forma, o economista está ativa e diretamente envolvido no *decision-making*, ou no *making of decisions*. Tem, pois, a missão de estudar o passado "for the sake of the present" e com um olho no futuro (p. 11), situando por esta via a economia na fronteira das ciências.

Pergunta-se: se A causa B, será que, se A não ocorresse, B não aconteceria? Na lógica formal se A implica B, então *n*ão B implica *n*ão A. É a equivalente contrapositiva. E, claro, <u>*não* A</u> não implica <u>*não* B</u>. Contudo, no mundo da construção teórica ou da explicação, admitindo que A causa B poderá dar-se o caso que se <u>*não* A</u>, então <u>*não* B</u>. Estamos, pois, na esfera da causalidade contrafactual, a qual nos permite explorar que se A causa B, então, sob determinadas condições, B não ocorrerá na ausência de A.

A causalidade contrafactual é, digamos, diferente da causalidade *original*. Segundo esta, todo o efeito ou evento tem obrigatoriamente uma causa, nem que seja divina. De forma distinta, a causalidade contrafactual dirá que todo o evento admite uma causa, na condição de o evento se encontrar rodeado de determinadas circunstâncias. Neste contexto, as circunstâncias não são exatamente um dado; pelo contrário, são uma construção da mente.

Objeto de grande interesse, a procura da causa dos eventos gerou desde logo uma atração muito especial pelo ensaio controlado, que rapidamente se aproximou do estatuto de *gold standard* também em economia. Motivou igualmente outras abordagens, designadamente a experimentação laboratorial, especialmente em contexto de sala de aula — com compreensíveis limitações, as quais, por sua vez, fizeram surgir um interesse bem mais promissor: a experimentação natural, a que voltaremos mais adiante.

Que o ensaio controlado não é imune à crítica é facilmente demonstrável, designadamente porque pode haver fatores relevantes não suficientemente controlados. Tome-se para ilustração a relação entre obesidade e ataque cardíaco, para dar um exemplo porventura mais entendível. Será que com base na observação de que os ataques cardíacos são mais frequentes entre obesos é lícito recomendar o uso de dieta? Se se der o caso de que os indivíduos com, digamos, coração mais fraco, precisam de mais gordura como proteção, então a dieta agravará o problema. Ou talvez possa haver um qualquer vírus que provoque simultaneamente ataque cardíaco e mais acumulação de gordura no corpo, situação em que a dieta manifestamente não resultaria. São meras especulações, que servem apenas para mostrar as dificuldades em estabelecer uma relação causal, que nem a forma mais acabada de ensaio clínico (o *double-blind randomized trial*) estará em condições de resolver plenamente.

O ensaio controlado levanta problemas adicionais em Economia, decorrentes de obstáculos de ordem financeira, política e ética, ou porque a população alvo resulta demasiadamente pequena. E face a estas limitações – especialmente as primeiras –, a experimentação laboratorial controlada em ambiente de sala de aula pode constituir uma alternativa.

Imagine-se que se pretende testar a existência da célebre *mão invisível* de Adam Smith. Um teste possível à eficiência das decisões descentralizadas consiste em atribuir a cada um dos alunos participantes na experimentação o estatuto de comprador ou vendedor, com os respetivos valores ou preços de reserva, e ver o que acontece ao fim de um certo número de transações, admitindo-se que em cada transação compradores e vendedores terão de licitar de acordo com a valorização individual do produto que querem comprar ou vender. Se o preço teórico de equilíbrio entre procura e oferta (antecipável pelo experimentador, dado o seu conhecimento das valorizações individuais de partida) for confirmado, teremos uma boa prova de que o mercado resultante de decisões descentralizadas funciona — pelo menos no caso de um mercado com as características de *double oral auction*, cujo exemplo acabado é a Bolsa de Valores de Nova Iorque.

Ainda que este resultado seja mais geral, isto é, mesmo que a simulação laboratorial possa ser aplicável a mercados com outras caraterísticas, por exemplo às situações de negociação bilateral, a experimentação laboratorial em economia será sempre de alcance limitado.

Estas limitações abriram então espaço à terceira via já referida – a experimentação natural – e que consiste no aproveitamento de uma variação relevante de contexto para fins de identificação de um determinado efeito causal.

Para uma ilustração rápida desta abordagem, tome-se o caso dos dois Estados alemães constituídos em 1949: a República Federal da Alemanha (RFA) e a República Democrática Alemã (RDA). Certamente que estes dois países, formados no pós-guerra, tinham à partida muito em comum, não se devendo a separação à escolha livre dos cidadãos dos países tornados independentes. Mais óbvio ainda é o facto de os dois países terem adotado soluções institucionais muito distintas. Neste quadro, poderá perguntar-se se a comparação das respetivas *performances* económicas não constituirá um bom indicador do papel das instituições na prosperidade económica, embora, adiante-se, com a limitação de que a RFA talvez tenha herdado uma base industrial mais sólida, para não falar de diferenças na tradição religiosa, conhecida a maior prevalência da igreja católica na Alemanha ocidental (Morck and Yeung, 2011, pp. 43-44).

Este exercício – e outros análogos – é pleno de engenho e de arrojo. Contudo, descartar a causalidade contrafactual, defender que a inferência contrafactual não é realizável, conduz a uma posição de extremo pessimismo, que, no limite, nega à ciência económica o estatuto de teoria falsificável, a um passo, portanto, da afirmação que "theory is evidence too!" (Card e Kruger, 1995, p. xi). Dominante de alguma forma nos anos 50 a 90, este último entendimento, mais cético, fez com que a análise da causalidade estivesse por um longo período fora da agenda do economista encartado. Em reação exagerada, a causalidade em economia tornou-se depois tão dominante que chegou ao ponto de parecer que para o economista académico pouco mais existe.

Em suma, mantendo-se o interesse em explicar os eventos, a causa dos eventos, não haveria outro remédio senão fazer o melhor uso possível da observação. Só para ilustrar o desafio que esta abordagem coloca, seria evidentemente muito ingénuo se, para estudar o efeito do salário mínimo sobre o emprego, apenas comparássemos a média de emprego nos estados/países com salário mínimo com a média dos estados sem salário mínimo. Tecnicamente dir-se-ia que são muitos os *confounders* – ou fatores de confusão ou de confundimento – para os quais se torna necessário controlar, porque uma coisa é a diferença entre as duas médias assim calculadas e outra bem distinta é saber que fração da diferença observada no nível de emprego pode ser atribuída à existência do salário mínimo. A dificuldade está, pois, na possível existência de fatores que induzem conclusões erradas: fatores ou variáveis que afetam simultaneamente o tratamento – o salário mínimo – e a variável de resultado – o emprego –, suscetíveis de introduzir concomitância ou correlação positiva entre as duas variáveis, circunstância que não permite ao decisor político assegurar que subindo o salário mínimo o emprego, ao invés, não diminua.

A dificuldade aguça o engenho. Um primeiro passo consiste em admitir que tudo o que é relevante é observável. Se participantes e não participantes de um programa de formação profissional registarem os mesmos valores para os *confundidores*, então a diferença de resultados entre os dois grupos pode identificar o efeito causal (Athey e Imbens, 2017, p. 5). A não observação de tudo o que teoricamente é relevante constitui, porém, um extraordinário complicador para o qual só existe uma solução: a admissão de premissas adicionais.

A causalidade é, assim, um verdadeiro produto da mente, "a thought experiment", como dizia James Heckman (Nobel em 2000), de onde resulta que a análise causal não é uma mera operação estatística, pois na verdade um analista versado apenas em estatística estará com certeza mal equipado para estabelecer uma relação causal em economia (Heckman e Pinto, 2022, p. 21).

O Efeito Causal do Salário Mínimo Sobre o Emprego

Retome-se, para primeira ilustração da causalidade contrafactual, o efeito do salário mínimo sobre o emprego.

Em primeiro lugar, bem se pode perguntar se faz sentido a discussão. É famosa a afirmação de George Stigler, Prémio Nobel em 1982: "one evidence of professional integrity of the economist is the fact that it is not possible to enlist good economists to defend (…) minimum wage laws" (Stigler, 1982, p. 60); com isto pretendendo evidentemente dizer que a subida do salário mínimo leva necessariamente à destruição de empregos. Como poderia a procura (de trabalho) não diminuir se o preço aumenta?

É assim facilmente compreensível a polémica criada por um estudo célebre de David Card e Alan Krueger, publicado em 1994, na *American Economic Review*, onde se afirmava perentoriamente: "we find no indication that the rise in the minimum wage reduced employment."

Em português para que fique claro: não há evidência que indique que uma subida do salário mínimo reduza o emprego. Uma polémica logo reavivada com a publicação, no ano seguinte, do livro Myth and Measurement: The New Economics of the Minimum Wage (Card e Krueger, 1995), ao ponto de Merton Miller, que com Franco Modigliani foi prémio Nobel em 1985, em tributo do famoso teorema Modigliani-Miller sobre a estrutura ótima do capital, vir a terreiro em tom acusatório: "I tremble for my profession" (Miller, 1996). James Buchanan, outro Prémio Nobel, mais expressivo, dizia: "Fortunately, only a handful of economists are willing to throw over the teaching of two centuries;" e acrescentava, em linguagem imprópria: we have not yet become a bevy of camp-following whores" (Buchanan, 1996). Este debate acalorado talvez pareça surpreendente, mas não tanto assim se tivermos em atenção que estava em causa algo muito importante: a teoria de preços neoclássica.

A proposta inovadora de Card e Krueger consistia em explorar as virtudes da experimentação natural, em mostrar como a subida unilateral do salário mínimo nos pode dizer muito mais do que a teoria *standard* tradicional. A estratégia de modelação passava então por avaliar o emprego nos restaurantes de comida rápida em New Jersey, antes e depois da intervenção legislativa que fez aumentar de uma só vez o salário mínimo por hora em quase 20%, para depois comparar a variação assim obtida com a variação observada nos restaurantes homólogos situados numa certa vizinhança mas pertencentes a um outro estado (a Pensilvânia), onde o salário mínimo não sofreu, por lei, qualquer modificação no período considerado.

Aparentemente contraintuitivo, o efeito não negativo sobre o emprego era antecipável, no sentido em que desde Joan Robinson (1969) se conhecia que haveria circunstâncias em que tendo os empregadores poder de monopsónio (isto é, a capacidade de pagar ao trabalhador abaixo do que determinaria a sua produtividade), a introdução de um preço mínimo obrigatório podia até fazer subir a quantidade de mão de obra a recrutar.

Mais diferenciadora, contudo, é a constatação de que a teoria existente não permitia uma explicação cabal dos factos. Com efeito, seria plausível que, perante uma subida tão pronunciada do salário mínimo, o preço da refeição também subisse, repercutindo nos consumidores o custo adicional. Só que esta relação não foi detetada na proporção esperada. De facto, a subida do preço do hambúrguer não foi proporcionalmente maior nas empresas que inicialmente praticavam salários mais baixos (Card e Krueger, 1994, p. 792).

Os dados não eram assim compatíveis com os modelos disponíveis. Tinham, porém, o condão de gerar novas explicações alternativas, produzidas agora por indução mais do que por dedução, muito ao arrepio de toda a construção neoclássica, para a qual, no fundo, a construção teórica constituiria ela própria *evidência*.

Repare-se que a estratégia de apuramento do efeito causal do salário mínimo passou pela observação de unidades de produção similares, mas sujeitas a diferentes níveis de exposição ao tratamento. Uma inovação posterior, muito relevante, e aplicável a outros domínios da análise económica, consistiu em criar um grupo de controlo artificial, como resposta à possível falta de comparabilidade entre unidades *tratadas* e *não tratadas*. Na falta de um contrafactual apropriado, a solução poderia estar então em combinar *convexamente* unidades de controlo à partida imperfeitas, por forma a que o grupo resultante – sintético por definição – apresentasse maior comparabilidade. Estudos muito recentes utilizando esta técnica confirmam a não existência no contexto norte-americano de efeitos negativos da subida do salário mínimo sobre o emprego (Wiltshire et al., 2026).

Como adverte George Stigler, "new ideas are sold very much like new cars: by exaggerating their superiority over the older models" (Stigler, 1982, p. 111). Dito de outra forma: "umbleness won't do it". Um homem (ou mulher), demasiado receoso das suas proezas será ele próprio ineficaz e um desencorajamento para os outros (Hardy, 1967, p. 66). Certamente que há um pouco de tudo isto na atitude dos defensores dos efeitos potencialmente neutrais do salário mínimo com base em exercícios de natureza quase experimental. A polémica, essa, continua, e nem a morte trágica, por suicídio, de um dos seus autores, Alan Krueger, em 2019, parece ter arrefecido os ânimos. Mas se a ciência económica pretende afirmar-se como *policy science*, não há outra solução senão clarificar os efeitos causais.

O Efeito Causal da Sindicalização

Não menos controverso é o efeito causal dos sindicatos sobre o salário.

Enquanto voz coletiva, um sindicato influencia as condições de trabalho, os recrutamentos e as separações de trabalhadores e, em alguns contextos, os planos de reestruturação e o investimento das empresas. Apresenta-se, acima de tudo, como um determinante fundamental dos salários, admitindo-se que através da negociação coletiva a sua presença possa gerar um prémio salarial – um *markup* ou bónus que não existiria na sua ausência.

O efeito causal assenta na construção do contrafactual relevante. Logicamente, a uma dada empresa só é dado observar um único estado, de cobertura ou não cobertura por um instrumento de regulamentação coletiva de trabalho. Estando a empresa coberta por uma convenção coletiva e vigorando uma determinada tabela salarial, que salários seriam observados se pelo contrário a cobertura não existisse, eis a questão. Poder-se-ia apurar a média salarial não condicionada das empresas abrangidas e compará-la com a média das empresas não abrangidas e assim obter o *gap* ou hiato salarial. No entanto, da constatação de que os trabalhadores das empresas abrangidas por um determinado contrato coletivo auferiam em média, digamos, 10% acima dos trabalhadores das empresas não abrangidas, não decorre que estes últimos beneficiariam de um acréscimo de 10% se as suas empresas passassem a estar cobertas.

Vejamos uma ilustração com dados microeconómicos da Alemanha, esse povo de poetas, filósofos e músicos – "Vede'los Alemães, soberbo gado, / Que por tão largos campos se apacenta", dizia Camões (7.4).

A Alemanha apresenta um atrativo do ponto de vista analítico: em nenhum outro país tem tanta relevância a representação no local de trabalho através da presença de comissões de trabalhadores (*Betriebsrat*). Trata-se, na realidade, de um modelo dual em que coexistem sindicatos e comissões de trabalhadores, aos sindicatos cabendo a negociação coletiva a nível setorial, incluindo a reivindicação salarial e o direito à greve, enquanto às comissões de trabalhadores fica reservada a negociação das condições concretas de trabalho, sob a obrigação de *peace agreement*, isto é, sem possibilidade de recorrer à greve, um direito reservado em exclusivo aos sindicatos.

Evidentemente que neste contexto específico poderá haver lugar ao cálculo de dois prémios salariais distintos, associados, respetivamente, à cobertura por convenção coletiva (via sindicato) e à presença da comissão de trabalhadores. Com base em dados da Agência Federal para o Emprego (*Bundesagentur für Arbeit*), estimou-se, em trabalho em coautoria, que os respetivos prémios salariais seriam de 5,9 e 6,5%, ao que se juntaria um adicional de 4,3% caso as duas representações estivessem presentes na empresa (Addison, Teixeira e Zwick, 2010, Table 2). Dito de outra forma, estimou-se que um indivíduo a trabalhar numa empresa com comissão de trabalhadores e abrangida por contratação coletiva ganharia um adicional de aproximadamente 18% em relação à situação em que os dois tipos de representação estivessem ausentes.

A estimação do efeito sindical através da vigência ou não de convenções coletivas é delicada e não ausente de limitações, designadamente em situações em que a taxa de cobertura da contratação coletiva é dominante, por força, por exemplo, de mecanismos de extensão que alargam o âmbito da convenção a empresas e trabalhadores não signatários dos acordos.

Felizmente, para o analista, a cobertura da negociação coletiva não é universal. É possível, desde logo, observar entradas e saídas de empresas de acordos coletivos. Admitindo-se que, condicionada nas caraterísticas observadas, a variação de estatuto por parte da empresa é aceitavelmente exógena, estaremos em condições de avaliar o valor do prémio sindical por uma via alternativa. Com efeito, é de crer que a entrada em vigor de um acordo gere um acréscimo salarial em relação à situação em que os trabalhadores continuam não abrangidos; e, simetricamente, a saída de um acordo deverá provocar uma perda salarial em relação à situação em que a cobertura permanece.

Neste contexto, tome-se para variável de resultado a média dos salários praticados na empresa. Então, trata-se de calcular a diferença entre o salário médio dos *joiners* e dos *never members* (para utilizar a linguagem anglo-saxónica, mais sintética); ou, simetricamente, a diferença entre *leavers* e *stayers*, em que *never members* e *stayers* são tomados como os respetivos contrafactuais.

A construção dos contrafactuais é decisiva e, mais uma vez, se adota a hipótese de que com dados microeconómicos suficientemente ricos é possível condicionar satisfatoriamente quer os grupos expostos a tratamento quer os grupos de controlo e desta forma assegurar que as diferenças salariais estimadas dizem respeito a grupos comparáveis.

Utilizando esta estratégia, foi possível apurar (Addison, Teixeira, Evers e Bellmann, 2014) que a passagem do cenário de não cobertura para uma situação de cobertura por convenção coletiva fez subir o salário médio entre 3 e 5%, verificando-se uma variação praticamente da mesma magnitude, mas de sinal contrário, no caso da passagem de cobertura para a situação de não cobertura.

Posto isto, e perante a dúvida legítima sobre o real efeito da sindicalização via celebração de convenções coletivas, em conjugação ou não com o efeito associado à presença de comissões de trabalhadores, tem cabimento a exploração de outras estratégias alternativas que possibilitem uma estimativa do efeito causal com porventura menos contaminação.

Uma ideia que logo ocorreu a alguns analistas foi a de explorar os resultados eleitorais em situações em que os trabalhadores são chamados a votar a favor ou contra a representação sindical. Consideremos os casos de votação muito equilibrada, em que a vitória (ou derrota) se decide por uma pequena margem. Não oferecerão as empresas em que a votação foi desfavorável o contrafactual ideal para as empresas em que a votação, pelo contrário, foi favorável? Se, digamos, por um triz se ganhou e por um triz se perdeu, não será realista presumir que afinal o estatuto de *participante* foi atribuído de forma aproximadamente aleatória?

Neste quadro, para estimar o efeito sindical bastaria então um número suficientemente grande de registos eleitorais. Usando este tipo de experimentação natural Dinardo e Lee (2004) concluíram que o prémio sindical nos Estados Unidos da América seria muito pequeno, possivelmente nulo. Um pequeno choque para muitos analistas, ainda hoje descrentes da fiabilidade desta estratégia de identificação. Certamente que se todas as empresas norte-americanas partilhassem desta ideia de que o efeito da sindicalização sobre os salários é negligenciável, não seria compreensível a férrea e persistente campanha contra os sindicatos por parte de muitas empresas e também de governos mais conservadores, bem ilustrada nas palavras de um governador estadual, que perante o respetivo Congresso, em janeiro de 2024, no *State of the State address*, afirmava "We will not let our state's economy suffer or become colateral damage as labor unions seek to consume new jobs." – acrescentando para que não ficassem dúvidas: "We will fight, all the way to the gates of hell. And we will win."[4]

A ideia de utilizar uma certa descontinuidade nos dados para identificar um determinado efeito mostrou-se atrativa em outros domínios. É o caso dos *Pactos para a Competitividade e o Emprego,*[5] acordados entre empresas e trabalhadores. Trata-se, neste caso, de testar os possíveis efeitos originados pela crescente descentralização dos processos de negociação coletiva. Se uma dada redução da taxa cobertura da contratação coletiva a nível sectorial for acompanhada, admitamos, por um aprofundamento da negociação bilateral ao nível da empresa, e daí resultarem benefícios para ambas as partes, talvez se possa falar com propriedade em *descentralização organizada,* em vez de uma *descentralização sem controlo.*

Por definição, um pacto para a competitividade e o emprego é mais do que uma mera concessão negocial; é mais do que aquela situação em que um acordo de âmbito setorial, estabelecido entre sindicatos e associações empresariais, deixa margem para a negociação ao nível da empresa, porventura permitindo um tratamento menos favorável, verificadas determinadas circunstâncias muito excecionais. Com efeito, um pacto não é um simples instrumento de flexibilização de acordos sectoriais, visando uma melhor adaptação da empresa a situações de especial urgência. Os pactos não se encontram, pois, limitados a situações de crise, e resultam no caso mais geral de algo que decorre da iniciativa das partes que, de forma autónoma, decidem consensualizar políticas dirigidas, no imediato e a médio prazo, à estabilidade da relação de emprego e à competitividade da empresa.

O exercício em que participei (Addison, Teixeira, Evers e Bellmann, 2017), consistiu na observação ao longo de um período de 4 anos de um conjunto de empresas com acordos celebrados no início da janela de observação. Observou-se também o respetivo grupo contrafactual, constituído por empresas envolvidas em processos de negociação mas sem acordo final.

O objetivo consistiu, então, em saber em que medida a celebração de um pacto conduziu a ganhos salariais, por comparação à situação de ausência de pacto; ou em que medida as

[4] O discurso do Governador Henry McMaster pode ser consultado em https://www.youtube.com/watch?v=0lriGjT5Hjw.

[5] Em língua alemã, Bündnisse für Arbeit und Wettbewerbsfähigkeit.

empresas participantes revelaram uma taxa mais elevada de sobrevivência, uma maior taxa de crescimento do emprego, do investimento ou da inovação. Os efeitos foram medidos a um, dois e três anos, e a conclusão principal foi que em nenhum caso existia evidência de resultados negativos; pelo contrário, era altamente provável que um pacto melhorasse significativamente o nível salarial médio dos trabalhadores, o volume de emprego, o investimento e a inovação.

O Efeito Causal das Práticas de Gestão

Os Pactos para a Competitividade e o Emprego ilustram a importância de certas práticas de gestão no contexto de uma determinada relação entre a gestão e a representação formal de trabalhadores no local de trabalho. Servem para mostrar os possíveis benefícios resultantes da atuação concertada entre parceiros, as vantagens da cooperação em vez da confrontação.

As práticas de gestão poderão também ser analisadas de uma forma mais geral, com ou sem relação direta com o tipo de representação. Sendo bem conhecida a dificuldade em explicar a persistente heterogeneidade nas práticas de gestão, a evidência indica, todavia, que elas podem explicar mais de 20% da variação observada na produtividade, bem acima da percentagem atribuída ao investimento em I&D, tecnologias da informação ou capital humano, por exemplo.

Felizmente, a conjugação de dados de inquéritos com a experimentação natural tem permitido afinar o efeito das práticas de gestão no desempenho das empresas. Tem igualmente permitido avaliar em que medida a gestão pode ser afetada pela regulação das relações laborais. Em termos simplificados, as *melhores práticas* são intervenções no domínio da gestão dos recursos humanos, com destaque para a monitorização e políticas de incentivos. Por definição, as melhores práticas beneficiam a produtividade em todo e qualquer local de trabalho, tratando-se neste sentido de verdadeiras práticas científicas de gestão.

Há, assim, e em primeiro lugar, que inquirir no terreno. Vejamos um exemplo de uma prática de gestão, retirada do Inquérito às Práticas de Gestão de 2022, a versão portuguesa do *World Management Survey*: "[e]m caso de identificação de situações de baixo desempenho, existiu algum tipo de consequência para as pessoas ao serviço? E seguem-se três opções: programa intensivo de formação; realocação ou colocação noutras funções; e cessação do contrato de trabalho."

Em segundo lugar, há que recorrer a fontes de informação complementar, de natureza longitudinal, para extração de características individuais, de trabalhadores e de empresas. Este passo é decisivo, porque sem acompanhamento individual não será possível distinguir os méritos de uma dada prática da qualidade intrínseca de um gestor ou de um qualquer trabalhador.

A qualidade intrínseca do gestor não é observável pelo analista. Mas um bom gestor é premiado pelo mercado e aufere um salário mais elevado. O salário é, assim, a valorização das características produtivas e é, obviamente, observável. A qualidade intrínseca pode assim ser estimada, para o efeito bastando admitir que o atributo acompanha o indivíduo nos seus diferentes postos de trabalho. A condição fundamental é, pois, o registo da mobilidade revelada no mercado de trabalho. E da mesma forma se procede para estimar a qualidade intrínseca dos não gestores.

Em trabalho recente utilizando o Inquérito às Práticas de Gestão, em cruzamento com dados microeconómicos, mostramos que o desempenho da empresa depende do uso das melhores práticas – mas também da qualidade média dos gestores e da qualidade média da força de trabalho (Addison, Carneiro e Teixeira, 2025). Confirmou-se ainda que a adoção das melhores práticas se traduziu sobretudo em políticas diferenciadoras no domínio do recrutamento e seleção, e por políticas que permitem fluxos líquidos de trabalhadores favoráveis, isto é, em que a qualidade dos que entram é superior à qualidade dos que saem.

Estas correlações podem, no entanto, ser fortalecidas com a utilização de contrafactuais relevantes, tirando partido de fatores externos que possam condicionar a adoção das melhores práticas.

Uma possível fonte de variação externa é a intervenção legislativa, que, designadamente no domínio da proteção do trabalho, pode induzir ou dificultar a representação coletiva dos trabalhadores, o seu grau de participação em decisões críticas, ou condicionar o direito à greve, por exemplo. E porque os representantes dos trabalhadores poderão favorecer determinadas políticas salariais em detrimento de outras, e ainda porque os representantes poderão ser mais ou menos favoráveis a políticas de incentivos individuais, resulta que as alterações legais poderão atuar como *drivers*, isto é, como inibidores ou desbloqueadores das práticas de gestão.

Tendo as alterações legislativas uma aplicabilidade geral e sendo a estabilidade das normas a regra, não parece ser possível recolher a variabilidade necessária se a evidência se limitar a um único país. Mas há variabilidade suficiente entre países europeus, o que possibilita a quase-experimentação. Um primeiro passo consiste no registo das alterações legislativas, o que pode ser feito através do Labour Regulation Index de Cambridge (Adams et al., 2023), enquanto para a recolha das práticas de gestão está disponível o European Company Survey (European Foundation for the Improvement of Living and Working Conditions, 2015), um inquérito europeu que contempla amostras representativas de estabelecimentos em 28 países, incluindo o Reino Unido. Utilizando estas duas fontes foi então possível codificar quer as alterações nas legislações nacionais, quer as variações nas práticas de gestão a nível microeconómico, assim se constituindo a base para o exercício de avaliação do impacto do *business environment* nas práticas de gestão.

Perante a evidente dificuldade em comparar realidades nacionais muito distintas, há que puxar de algum trunfo escondido na manga. Se Portugal, admitamos, introduzir uma alteração legislativa no âmbito da proteção do trabalhador e estivermos interessados em avaliar os seus efeitos nas práticas de gestão, então, na falta de um país imediatamente comparável, poderá lançar-se mão a um contrafactual sintético, constituído pela combinação convexa de países selecionados através de um critério admissível. O comparador assim resultante apresentará, por construção, um grau de comparabilidade maior, pelo menos do ponto de vista de algumas características relevantes e observáveis. E se não estivermos totalmente seguros acerca do procedimento, é sempre possível lançar mão aos testes de falsificação, ou placebos, para utilizar de novo a linguagem típica dos ensaios clínicos controlados.

No caso dos Estados Unidos (Bloom et al., 2019), os estudos mostram que a introdução de Right-to-Work laws, isto é, a introdução de medidas legislativas desfavoráveis à representação sindical, levou a uma maior frequência de práticas de gestão com ênfase em incentivos individuais e políticas de recrutamento e despedimento mais seletivas. Para o conjunto dos países da União Europeia e Reino Unido, os resultados da investigação em que participei (Addison e Teixeira, 2025) mostram que mais desproteção dos órgãos representativos dos trabalhadores leva ao uso mais intensivo de práticas baseadas em incentivos individuais, enquanto o aumento da proteção conduz à sua diminuição.

A Causa da Riqueza das Nações

As instituições afetam os resultados económicos – é, pois, a conclusão a retirar. É a confirmação, no fundo, da ideia mais geral, segundo a qual a prosperidade económica depende da qualidade das instituições, uma ideia, curiosamente, já presente em Adam Smith. Regressamos, assim, à causa da riqueza das nações e à ilustração do caso especial das *experiências naturais históricas*.

O que pode então explicar a riqueza de uma nação? Acemoglu, Johnson e Robinson – prémios Nobel em 2024 – são perentórios: *Good institutions*. Claro que em primeira mão poderíamos pensar na escolaridade média como fator causante. Com efeito, parece evidente a relação entre taxa de escolarização da população e PIB *per capita*. No entanto, se repararmos bem, veremos que a taxa de retorno – ou taxa de rendimento individual – se encontra entre 6 e 10% por ano adicional de escolaridade, uma estimativa válida para países desenvolvidos e menos desenvolvidos, no que constitui provavelmente a regularidade empírica mais robusta em economia. Ora, dado que a diferença na escolaridade média entre países mais ricos e países mais pobres é de aproximadamente 8 anos, a existir um papel determinante e causal da escolaridade na explicação da prosperidade económica, tornar-se-ia necessário admitir externalidades do capital humano muito elevadas. Com efeito, Acemoglu and Angrist (2000, pp. 10-11) calculam que para se poder explicar a desigualdade entre países ricos e países pobres seriam necessárias externalidades entre 25 e 30%. Não há, todavia, qualquer evidência que aponte para esta ordem de grandeza, situando-se as melhores estimativas entre 1 e 3% por ano adicional de escolaridade média.

Em todo o caso, para estabelecer uma possível relação entre escolarização e riqueza, é preciso em primeiro lugar assegurar que mais escolaridade conduz a rendimentos salariais mais elevados ao longo da vida ativa. Para este fim, pode recorrer-se à variação na escolaridade mínima obrigatória como fonte de identificação da relação causal, em novo golpe quase-experimental.

No caso português, em 1974, a escolaridade mínima obrigatória estava fixada em 6 anos. Dado que a idade de entrada na escola se situava nos 7 anos, vem que uma criança poderia abandonar a escola aos 13 anos. Hoje em dia, entrando aos 6 anos, será necessário completar 18 anos ou concluir o 12.º ano de escolaridade. Tem-se assim que, pela via do aumento gradual da escolaridade obrigatória, podemos observar diferenças no nível de escolaridade de 1, 2 ou mais anos em indivíduos com saída precoce do sistema de ensino.

Repare-se que, neste contexto, os grupos de controlo e de teste são criados *naturalmente*. De facto, se num dado ano t a escolaridade mínima obrigar a permanecer na escola até aos 15 anos, em vez de 14, então, no universo dos *high-school dropouts*, os que completarem 14 anos antes do ano t constituem o grupo de controlo, enquanto os que completam 14 anos após o ano t formam o grupo de tratamento. Estimativas usando esta estratégia permitem concluir que os ganhos salariais do grupo de tratamento – excedem os ganhos salarias do grupo de controlo, pelo que a conclusão é que a escolaridade definitivamente compensa.

Como estratégia alternativa de estimação do efeito causal da aquisição de escolaridade há ainda a possibilidade de recorrer ao trimestre de nascimento. Também neste caso se trata de encontrar variação exógena na escolaridade, considerando muito naturalmente que o trimestre de nascimento não influencia os ganhos salariais potenciais (descartada a influência dos astros…). Com efeito, conjugando a idade mínima de entrada na escola com a duração da escolaridade mínima obrigatória, tem-se que os que nascem no primeiro trimestre poderão sair da escola mais cedo, por comparação com aqueles que nascem no 4.º trimestre, pelo simples facto de que, tendo os primeiros entrado relativamente mais velhos, atingem mais depressa o limite de idade de permanência obrigatória na escola. A população alvo é novamente composta por potenciais *dropouts*, isto é, por todos aqueles que apenas por obrigação legal se encontram a frequentar a escola.

Seguindo esta estratégia, Angrist and Krueger (1991) chegam a um resultado extraordinário: no grupo alvo, a taxa individual de retorno por um ano extra de escolaridade encontra-se compreendida entre 6 e 10%, ou seja, é da mesma ordem de grandeza da estimativa para toda a população.

Ficando assim estabelecida a magnitude do efeito causal da escolaridade sobre os ganhos salariais individuais, e tendo em conta a presença de externalidades significativamente abaixo da taxa de retorno individual, conclui-se que a causa maior da prosperidade – e da desigualdade entre países – terá de ser outra que não o nível de escolarização.

A hipótese lançada por Acemoglu, Johnson e Robinson, como se disse, é que a causa da riqueza das nações se encontra na qualidade exibida pelas instituições políticas e económicas nacionais, supostamente – e creio que fundamentadamente – muito desiguais. Para demonstrar esta ligação, recorre-se a uma ideia simples – mas novamente engenhosa – de que as instituições contemporâneas resultam, pelo menos em parte, de determinados acontecimentos históricos.

Com base numa amostra muito alargada de 64 países (ex-colónias da mais variada origem) constatou-se algo muito curioso – que a variação no PIB *per capita* estava associada à variação na taxa de mortalidade dos primeiros colonos. E no sentido em que, quanto maior a taxa de mortalidade então observada, menor o PIB *per capita* das nações hoje independentes.

Com esta evidência na mão, Acemoglu, Johnson e Robinson exploraram a seguinte cadeia causal: a mortalidade dos primeiros colonos afeta o tipo de colonização, o tipo de colonização afeta as instituições coloniais nascentes e, tendo persistido, as instituições iniciais formam a base das instituições atuais.

Na prática o exercício consiste em testar a relação entre qualidade das instituições e PIB *per capita* atuais, escolhendo-se para indicador da qualidade institucional o Índice do Estado de Direito, acessível através do World Justice Project, entre muitas outras alternativas. Subentende-se aqui que um risco elevado de expropriação, por exemplo, não constitui um bom indicador de segurança económica ou um bom incentivo ao investimento empresarial, ao mesmo tempo que se considera provável que a insegurança se encontre correlacionada com a presença de instituições coloniais iniciais mais frágeis (e mais extractivas).

E a conclusão é que "institutions matter". Estimou-se que o efeito causal das instituições sobre a prosperidade económica, medida em PIB *per capita* em PPP, é de grandeza máxima, ao ponto de, por exemplo, se a Nigéria dispusesse de instituições qualitativamente semelhantes às do Chile, poderia ver multiplicado por 7 o seu PIB per capita (Acemoglu, Johnson e Robinson, 2001, p. 1371). À época em que o estudo foi desenvolvido o rendimento per capita do Chile era 11 vezes maior do que o da Nigéria, de onde resulta que só pela via da melhoria do quadro institucional a Nigéria ficaria quase tão próspera quanto o Chile!

Trata-se de mais um resultado extraordinário, vertido mais tarde em *best-seller*, intitulado *Porque Falham as Nações* (Acemoglu e Robinson, 2013). Bastará, contudo, aqui sublinhar a virtude da estratégia de modelação, assente na utilização de um *natural historical experiment*, na experimentação natural com base em *chance events* e traduzida na capacidade em mostrar como acontecimentos históricos relevantes, combinados com os métodos da ciência económica, podem ser de grande relevância para a compreensão de fenómenos complexos.

Mas que não se encontre aqui qualquer determinismo imobilizador ou predestinação. A causalidade encontrada a partir de um contrafactual construído pela mente diz respeito ao passado, não determina as decisões a tomar no presente visando a defesa do futuro — determinismo no sentido apenas em que não há eventos que não possamos tentar explicar e, nessa medida, o exercício contrafactual é verdadeiramente libertador porque guia o *making of decisions*.

As instituições são alteráveis e, para nosso espanto, até as democracias morrem, como mostra o último Relatório da Democracia 2025, onde se refere que, pela primeira vez nos últimos 30 anos, há no mundo mais autocracias do que democracias.[6] As escolhas estão, pois, sempre em aberto, embora fiquemos prisioneiros inelutavelmente das suas consequências.

Concluo assim esta apologia do *saber de experiências feito* (Camões, 3. 4):

E, pera dizer tudo, temo e creio
Que qualquer longo tempo curto seja:
Mas, pois o mandas, tudo se te deve;
Irei contra o que devo, e serei breve.

Temo que não o tenha sido.

[6] De acordo com o Relatório da Democracia 2025 (Instituto de Variedades de Democracia – V Dem), em 2025 haveria 88 democracias eleitorais e 91 autocracias. Utilizando o critério mais exigente de democracia liberal, o número de democracias decresceria para cerca de 1/3, ou para um total de 29.

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The Role of Technology Extension and Transfer in Firms' Innovation and Productivity in Peru

O Papel da Extensão e Transferência de Tecnologia na Inovação e Produtividade das Empresas no Peru

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ABSTRACT
This study examines how technology extension and transfer services (TETS) drive firm-level innovation and productivity. Since research and development (R&D) investments are subject to market failure, engaging with external agents enables firms to innovate at lower risk and cost. Using data from Peru's National Innovation Survey (ENI), we apply the Crépon, Duguet, and Mairesse (CDM) model alongside propensity score matching (PSM) to enhance the reliability of our results. Additionally, we employ the generalized propensity score (GPS) method to analyze the sensitivity of innovation and sales outcomes to varying investment levels. The findings confirm that investment in training and external R&D significantly enhances innovation, thereby boosting labor productivity. However, this relationship is nonlinear, suggesting the presence of investment thresholds required to maximize impact.
Keywords: Technology Transfer; Innovation; Productivity; R&D; CDM model

JEL Classification: L25, O32, O38

RESUMO
Este estudo analisa como os serviços de extensão e transferência de tecnologia (SETT) impulsionam a inovação e a produtividade a nível empresarial. Dado que os investimentos em investigação e desenvolvimento (I&D) estão sujeitos a falhas de mercado, a colaboração com agentes externos permite às empresas inovar com menor risco e custo. Utilizando dados da Encuesta Nacional de Innovación (ENI) do Peru, aplicamos o modelo de Crépon, Duguet e Mairesse (CDM) com o método de propensity score matching (PSM), para reforçar a robustez dos resultados. Adicionalmente, usamos o método do generalized propensity score (GPS) para analisar a sensibilidade da inovação e das vendas a diferentes níveis de investimento. Os resultados confirmam que o investimento em formação e em I&D externa aumenta significativamente a inovação, melhorando assim a produtividade do trabalho. No entanto, esta relação é não linear, sugerindo a existência de limiares de investimento necessários para maximizar o impacto.
Palavras-chave: Transferência de Tecnologia, Inovação, Produtividade, I&D, Modelo CDM

1. Introduction

Firms that invest in innovation follow one of four strategies (Lipczynski et al., 2017). An offensive strategy seeks to lead the market by introducing recent technology, requiring substantial investment in equipment and human capital. A defensive strategy is adopted to counteract a competitor's technological shift, ensuring survival in a changing market. An imitative strategy focuses on replicating existing innovations, typically through licensing agreements or by leveraging publicly available knowledge. A dependent strategy positions firms in a subordinate role, such as serving as suppliers or subcontractors, adopting technology provided by the contracting firm.

Research and development (R&D) plays a vital role among key innovation activities. Firms typically establish dedicated R&D units with specialized laboratories, qualified personnel, and structured research programs. However, a sizable proportion of firms – particularly small and medium-sized enterprises (SMEs) – lack the financial and organizational capacity to undertake such investments. High initial costs, risk exposure, and uncertainty regarding results create significant barriers. In addition, smaller firms face structural challenges in accessing financing, developing industry linkages, and attracting specialized human capital (Shapira and Youtie, 2016). These market failures constrain the emergence of potentially innovative firms and slow the pace of industrial innovation.

Innovation is a key driver of productivity growth (Syverson, 2011). One of the most widely used empirical frameworks for analyzing the relationship between R&D, innovation, and productivity is the Crépon, Duguet & Mairesse (CDM) model (Crépon et al., 1998). This model has been extensively applied in demonstrating the positive link between innovation and productivity in advanced economies (Lööf et al., 2017). However, findings in emerging market economies (EMEs) have been mixed. While studies consistently confirm a direct relationship between innovation and productivity, the link between R&D investment and innovation is less robust (Fedyunina and Radosevic, 2022). This suggests that EME firms often engage in innovative processes through alternative investment pathways, such as collaborations with other firms or research institutions, rather than relying solely on in-house R&D.

These collaborative dynamics contribute to the formation of an innovation ecosystem, where firms leverage external knowledge while developing internal competencies – an approach known as open innovation. In the era of Industry 4.0, open innovation has become one of the most viable mechanisms for fostering both knowledge generation and technology commercialization. Within this framework, technology transfer – the process by which scientific and technological discoveries are transmitted from one organization to another for further development and commercialization – plays a crucial role in enhancing firms' absorptive capacity and strengthening innovation capabilities in EMEs (Alkhazaleh et al., 2022).

Similarly, technology extension services provide direct support to firms in technological upgrading and innovation adoption, with a particular focus on SMEs (Shapira et al., 2015). These services aim to enhance firms' competitiveness by improving business management practices, production processes, and access to specialized technological knowledge. They also provide targeted consulting services, technical assistance, workforce training, and support for the development of innovation-driven projects (De Groote, 2016).

Kolodny et al. (2001) differentiate between technology transfer, defined as the commercialization of complex technologies by research laboratories and R&D centers for large industrial firms, and technology extension, which focuses on providing applied technological support to SMEs. Two core components of these mechanisms are external R&D acquisition and training services for technology adoption. Firms that engage with these services benefit from greater access to innovative technology, the introduction of new products and services, and improvements in overall performance in the short and medium term (Shapira and Youtie, 2016).

As a developing economy, Peru faces structural constraints that hinder technological progress and productivity growth. Its total factor productivity (TFP) represents less than 30% of that of the U.S. (Loayza, 2016) and R&D investment accounts for just 0.11% of GDP, making it one of the lowest in Latin America (CONCYTEC, 2017). These low investment levels are reflected in Peru's performance in the Global Innovation Index (WIPO, 2021), where it ranked 70th out of 132 economies, with particularly weak results in knowledge and technology outputs (87th place).

This study quantifies the impact of technology extension and transfer services (TETS) – proxied by expenditures on innovation-related training and external R&D investment – on firms' innovation strategies and productivity performance, and seeks to answer the following hypotheses:

- H1: Does the decision to invest in TETS, and the amount invested, affect firms' innovation and productivity?
- H2: What are the differences and complementarities between TETS investment and internal R&D investment?

By addressing these questions, this study contributes to the expanding body of research in two key aspects:

i. First, it demonstrates that TETS represent a viable alternative for firms seeking to innovate with reduced risk and cost, particularly given the high uncertainty and market failures associated with internal R&D (Shapira & Youtie, 2016; Bukstein et al., 2018). In doing so, it contributes to the literature on the innovation process in Latin America, which suggests that firms in EMEs utilize investment avenues alternative to internal R&D – such as TETS collaborations—to foster innovation and enhance productivity. While the use of total investment in STI has been proposed in the Latin American context to evaluate innovation outcomes, there is a distinct lack of specific studies addressing the differential effects of each individual type of innovation activity.
ii. Second, to mitigate potential model endogeneity issues (Chudnovsky, 2006), the study employs a sophisticated methodological framework to yield robust and granular results. Specifically, it utilizes an adjusted CDM model, conducting additional regressions on samples derived and weighted using Propensity Score Matching (PSM) and Generalized Propensity Score (GPS) to analyze the differential effects across varying investment intensities in TETS and internal R&D.

The paper is structured as follows: Section 2 presents a review of the relevant literature; Section 3 describes the dataset and variables; Section 4 details the econometric methodology; Section 5 discusses the results and hypothesis validation; and finally, the study presents its main findings.

2. Literature Review

2.1. Relationship between innovation activities, innovation, and productivity

Investing in innovation activities aims to create or expand knowledge within an organization. Pakes and Griliches (1984) highlight that in the transition between R&D investment and its effects on innovation and productivity, an unobservable variable – knowledge capital – plays a crucial role. This variable is defined as the economic value of technological knowledge. The accumulation of knowledge depends on R&D expenditures, underlying trends, and variations in research productivity. Investment in R&D affects knowledge capital with a time lag, accumulating over previous years. In turn, knowledge capital drives innovation outcomes.

Crépon et al. (1998) model the relationship between R&D, innovation, and productivity using a structural framework with three key linkages: (i) the relationship between R&D and its drivers, (ii) an innovation equation linked to R&D, and (iii) a productivity equation linked to innovation. Empirically, this is evaluated using a four-stage regression model, where the first two components relate to firms' decisions to invest in R&D and the scale of investment. Their findings for French firms indicate that both the decision to invest in R&D and the amount invested are influenced by firm size, market diversification, market share, demand conditions, and technological opportunities. Regarding innovation, they find positive effects of R&D investment, as well as a positive relationship between innovation and productivity.

Lööf and Heshmati (2006) extend the CDM model in a study on Swedish firms, evaluating the robustness of the results across different estimation techniques, testing for consistency in both services and manufacturing, verifying results across alternative data sources, and addressing potential distortions from outliers. Their results confirm that all findings remain statistically significant across model specifications.

Research on EMEs has yielded mixed results. Ramadani et al. (2019) apply the CDM model to Eastern European economies and find that external knowledge acquisition—used as a proxy for R&D – positively influences product innovation, which in turn enhances labor productivity. However, in a separate study on Eastern Europe, Fedyunina and Radosevic (2022) find no statistically significant relationship between R&D investment, innovation, and productivity. They argue that in EMEs, production capabilities are more critical than R&D investment and test this hypothesis using an alternative model in which the former replaces the latter. Their findings indicate that production capabilities do not significantly impact innovation but do influence productivity. They conclude that R&D investment and production capability development follow distinct processes and that in EMEs, the latter is more relevant for productivity growth.

Edeh and Acevedo (2021) identify access to financing as the most significant barrier for firms in EMEs such as Nigeria. Using the CDM model, they find that R&D investment positively affects product and marketing innovation but has no significant impact on process innovation. Their results also indicate that while government funding does not significantly influence R&D investment, it does have a positive effect on productivity.

2.2. Relationship between tets and productivity

Bell (1984) argues that technological change in firms is also driven by learning processes, which can occur internally or externally. He identifies three mechanisms through which this occurs: (i) learning-by-training, where firms acquire knowledge through employee training programs; (ii) learning-by-hiring, where firms gain knowledge by recruiting skilled personnel; and (iii) learning-by-searching, where firms engage in research activities. These mechanisms involve firms establishing linkages with other entities, including suppliers, research centers, universities, and specialized institutions. Acquiring external knowledge enhances cost efficiency and revitalizes firms' knowledge bases (Chen et al., 2015).

Jarmin (1999) evaluates a technology extension program in the U.S. using a two-stage model. In the first stage, he finds that firms with high prior growth, but low productivity are more likely to use these services. The final results show positive effects on labor productivity, ranging from 3.4% to 16%. Ordowich et al. (2012) assess the same program using difference-in-differences and a lagged dependent variable model, also incorporating a firm survival model. Their results are inconclusive for the full sample, but a firm-size breakdown reveals positive effects. Finally, Lipscomb et al. (2018) conduct another evaluation of the program, incorporating updated datasets and methodological refinements. Their findings indicate that firms using these services see greater increases in sales and employment and are 18% less likely to exit the market.

Chen et al. (2015) examine four distinct types of external knowledge acquisition and their impact on innovation in Chinese firms. When analyzed individually, each type shows positive effects, though horizontal linkages have a weaker impact. When assessed jointly, all remain statistically significant, except for horizontal linkages. Additionally, when the model includes an interaction term for internal R&D, the impact is stronger for firms collaborating with supply chain partners or technology service providers. However, for horizontal linkages, the only significant effect appears in the interaction term, whereas the opposite is observed for science-based partnerships.

Hottenrott and Lopes-Bento (2016) find a positive but nonlinear relationship between external R&D and innovation, with diminishing returns as firms increase their reliance on kind of investment. Their findings suggest that the optimal share of external R&D participation in projects is around 60%. Carboni and Medda (2021) report comparable results for Germany, France, Spain, and Italy, arguing that excessive reliance on external services can discourage firms from investing in in-house research and developing internal capabilities. However, when external R&D is sourced within a business group, it has the strongest impact on product innovation performance compared to acquiring it from universities or other firms.

Workforce training programs also contribute positively to innovation. Na (2021) finds that on-the-job training and employees' education levels enhance all types of innovation across Eastern Europe and Central Asia. This relationship is demonstrated using a two-stage Heckman regression model.

2.3. Innovation activities, innovation, and productivity in latin america

For the Argentine case, Chudnovsky et al. (2006) report that between 1992 and 2001, the acquisition of external technology functioned as an innovation mechanism complementary to internal R&D, with a predominant incidence on the introduction of new processes. A counterintuitive finding of the study is the resilience of internal R&D expenditure in the face of economic crisis; the authors argue that this responds to the nature of technological knowledge as a strategic and cumulative asset that firms avoid divesting from during cyclical downturns.

Regarding six Latin American countries, Crespi and Zúñiga (2012) demonstrate that measuring innovative effort requires considering not only internal R&D, but also investment in innovation activities in a broad sense. Despite the observed heterogeneity in investment determinants, the study confirms that technological innovation increases labor productivity. This impact proves to be higher than that reported in industrialized economies, suggesting that firms in the region benefit from high returns associated with technological convergence (catch-up) given their distance from the global technological frontier.

Atayde et al. (2021) examine the impact of market competition on innovation and productivity in the Mexican manufacturing industry, a sector characterized by persistent barriers to entry. Their findings reveal a negative linear relationship between competition and innovation investment, in contrast to a positive effect on productivity. The authors suggest that this divergence indicates that, in the face of greater competitive pressure, firms substitute costly R&D investment for more immediate and cost-effective efficiency strategies, such as the adoption of managerial practices or other forms of non-technological innovation.

Other empirical studies have examined the effect of public support on business innovation. In the Colombian case, Busom et al. (2017), using an extension of the CDM model, found that public support increases both the probability of investing in innovation and the investment intensity, which in turn translates into significant effects on firm productivity through the introduction of innovations. On the other hand, Bukstein et al. (2018) applied a Difference-in-Differences and Propensity Score Matching (PSM) approach to data from Uruguay, finding that government subsidies increased the probability and amount of innovation investment (additionality or crowding-in effect) by 22% to 24%, although these effects were significant for only three years. While positive achievements were observed in technological innovation, no significant impacts were found on firm performance, such as labor productivity or exports.

In Peru, Tello (2020) examines the role of information and communication technologies (ICTs) adoption and differentiates between internal and external R&D investment. His findings indicate that decisions to invest in both types of R&D depend on firm size and whether the firm is part of a business group. The scale of investment is found to be significant for innovation outcomes, along with factors such as competitive pressure and mechanisms for protecting innovation. While productivity is positively influenced by innovation, its primary drivers are the capital-labor ratio and human capital accumulation. Internet use is also found to marginally increase the likelihood of innovation. The study concludes that firms are not fully capitalizing on the benefits of R&D and innovation activities.

García (2022) analyzes manufacturing firms to assess the impact of innovation and ICT adoption on productivity, measured using the Levinsohn and Petrin approach. Fixed-effects regression results indicate a positive relationship between investment in science, technology, and innovation (STI) and TFP. However, the effects of ICT adoption remain inconclusive, with significant results observed only for certain variables, such as local network usage, software acquisition, and the implementation of computerized management systems.

In summary, the innovation process in Latin American countries is characterized by the acquisition and adaptation of technology rather than the generation of new frontier knowledge. Consequently, a diverse range of activities is relevant for achieving innovation, such as design, the installation of new machinery, industrial engineering, embodied and disembodied technology, marketing, and training. While investment in business R&D remains low, it exerts a high impact on generating innovative results; therefore, governments often subsidize this activity, although the existence of underdeveloped National Innovation Systems constrains its effects on the innovation process.

3. Research Design and Methodology

3.1. Dataset

This study uses data from the National Innovation Survey (ENI) for manufacturing and knowledge-intensive services, conducted by Peru's National Statistics Institute (INEI) in 2018. The survey covers Peruvian firms with annual sales exceeding USD 189,405[1] and includes 2,084 firms, selected based on two criteria: (i) a mandatory sample covering firms that account for 81% of net annual sales in their respective industries, and (ii) a randomly selected, non-mandatory sample drawn from the remaining firms. The survey collects data on firm characteristics, innovation activities, human resources, financing, obstacles, and outcomes for 2015, 2016, and 2017.

3.2. Variable definitions

TETS adoption (gst_i) is measured based on whether a firm invested in external R&D and innovation-related training in 2015 and 2016. Investment intensity (rst_i) is calculated

[1] In Peru, firms are classified according to annual sales ranges (Supreme Decree No. 013-2013-PRODUCE). A micro-enterprise is defined as having declared annual sales of less than 150 Tax Units (UIT); small firms range between 150 and 1,700 UIT; medium-sized firms between 1,700 and 2,300 UIT; and large firms are those with sales exceeding 2,300 UIT. For the purposes of the ENI 2018, micro-enterprises were excluded from the sample. In that year, the UIT was valued at PEN 4,050 (approximately USD 1,263). As noted by Chudnovsky et al. (2006), small firms often engage in informal innovation activities that are difficult to capture or estimate through survey questionnaires; consequently, they are frequently excluded from the final sample in surveys of this nature.

as the logarithm of total investment over both years, divided by the number of employees. Innovation is measured using two variables. The first is a binary (dummy) variable (pst_i) that equals 1 if the firm introduced an innovation and 0 otherwise. The second is an innovation intensity variable (nst_i), defined as the share of total sales generated by innovative products. Labor productivity is captured as net sales per worker (Y/L), expressed in logarithms for 2017.

The independent variables (x) follow the original CDM model and its extensions (Edeh and Acedo, 2021; Lööf et al., 2017; Lööf and Heshmati, 2006; Ramadani et al., 2019). To incorporate a localized perspective, this study also draws on Peruvian research, including Tello (2020) and García (2022).

Firm size is measured by the number of employees, while human capital is defined as the percentage of employees with higher education. Market concentration is assessed using the Herfindahl-Hirschman Index (HHI). Once calculated, a categorical variable is assigned, classifying firms as unconcentrated (HHI < 0.15), moderately concentrated (0.15 ≤ HHI ≤ 0.25), or highly concentrated (HHI > 0.25) (Nguyen et al., 2020). These variables are used to test Schumpeterian hypotheses, which propose that larger firms and those operating in concentrated markets are better positioned to engage in innovation activities.

The analysis also accounts for market constraints, incorporating variables related to financing constraints, risk aversion, and technological and demand-side barriers. Other firm characteristics include firm age, as well as external linkages and international market participation, measured through foreign capital ownership and export activity.

For the innovation equation, additional controls include intellectual property protection, such as patents and copyrights, and participation in government programs. In the final stage, the model incorporates physical capital per worker, a key driver of productivity, alongside labor and human capital (Lööf and Heshmati, 2006; Jarmin, 1999). Following Lööf and Heshmati (2006), all monetary variables are expressed on a per-worker basis. A consumer price index (CPI) deflator is applied to adjust values to real terms over the three-year period.

Across all model specifications, additional controls include firm location, particularly whether the firm operates in Lima, given the city's concentration of TETS providers and access to transportation and communication networks. The analysis distinguishes between services and manufacturing, with further subdivisions based on technology intensity (UNIDO, 2019).

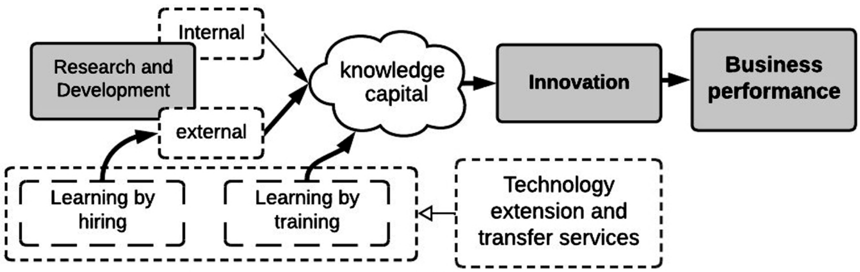
All the variables mentioned in this section and used in the CDM model are described in detail in the Annex.

3.3. Methodology

To test H1, the analysis applies the CDM model. The explanatory variables include the decision to use TETS and the intensity of investment, both measured as cumulative values for 2015 and 2016. By 2017, firms are expected to exhibit results in terms of innovation and productivity.

Figure 1, constructed from the literature, summarizes the causal chain of how different innovation activities, both R&D and TETS, increase knowledge capital, which in turn will have an effect on innovation and business performance of firms.

Figure 1. Process of R&D, TETS and innovation



Own elaboration based on Bell (1984) and Crépon et al. (1998).

A key challenge of the CDM model is the potential presence of endogeneity and selection bias (Crépon et al., 1998). This issue arises when the firms using TETS are not randomly selected but rather self-select into the program. As a result, the intensity of investment is only observed for firms that actively choose to engage with TETS, leading to a latent variable problem. To address this issue, the first stage of the analysis applies a Heckman selection model, where the decision to invest is treated as a latent variable (gst^*_i). The observed binary outcome (gst_i) takes a value of 1 if the firm chooses to invest and 0 otherwise:

$$gst_i = \begin{cases} 1 \ if \ gst_i^* > 0 \\ 0 \ if \ gst_i^* \leq 0 \end{cases} \tag{1a}$$

The intensity of investment in TETS (rst^*_i) is also a latent variable. The observed investment level (rst_i) is only recorded if the firm has chosen to use these services:

$$rst_i = \begin{cases} rst_i^* & if \ gst_i^* > 0 \\ unobserved & if \ gst_i^* \leq 0 \end{cases} \tag{1b}$$

Thus, both equations are related. In the classical version of the model, the latent variables are derived from the following equations:

$$gst_i^* = X_{0i} b_0 + u_{0i} \tag{2}$$

$$rst_i^* = X_{1i} b_1 + u_{1i} \tag{3}$$

the error terms (u_{0i} and u_{1i}) are potentially correlated (p) and assumed to follow a joint normal distribution. The correlation coefficient (p) is crucial for determining the interdependence between Equations (2) and (3). If $p = 0$, then the error terms are uncorrelated, and Ordinary Least Squares (OLS) would be a more efficient alternative. To correct for heteroskedasticity, robust standard errors are applied. Where X_{mi}, represent vectors of m firm characteristics and control variables (as defined in Section 3.2), and, b_0 are the corresponding vectors of parameters.

As a result, the first stage produces a predicted value for investment intensity, which is used in the second stage to examine the relationship between innovation and TETS investment. To estimate the innovation outcomes, we specify two distinct equations denoted by the subscript k. The first (k = 1) models product innovation (pst_i) as a binary outcome using a probit model. The second (k = 2) models innovation intensity (nst_i), defined as the share of sales from innovative products, using an OLS regression. In both specifications, the coefficient α_k captures the effect of the predicted investment intensity (rst^*_i) on the respective innovation output:

$$pst_i = \alpha_k rst_i^* + X_{2i} b_2 + u_{2i} \tag{4a}$$

$$nst_i = \alpha_k rst_i^* + X_{2i} b_2 + v_{2i} \tag{4b}$$

Both models consider innovation at all levels (internal, market, and international), following De Groote (2016), who argues that technology services, particularly TETS, primarily drive internal innovation rather than market-oriented innovation.

In the third stage, the analysis examines the relationship between predicted innovation outcomes (pst^*_i and nst^*_i) and labor productivity (q). The productivity measure is based on first differences between 2015 and 2017, following Pakes and Griliches (1984), who model R&D investments as lagged and cumulative inputs. This approach is also consistent with Jarmin (1999), assuming a Cobb-Douglas production function.

$$\Delta \ln q_i = \Delta \ln \frac{Y_i}{L_i} = \ln \frac{Y_{i,2017}}{L_{i,2017}} - \ln \frac{Y_{i,2015}}{L_{i,2015}} \tag{5}$$

where Y_i represents the net sales of firm i and L_i denotes the number of employees. First differences are also applied to physical capital per worker (K_i), employment (L_i), and human capital (H_i). following Lööf and Heshmati (2006):

$$\Delta \ln q_i = \Delta \ln \frac{Y_i}{L_i} = \varphi_1 pst_i^* + \delta \Delta \ln\left(\frac{K_i}{L_i}\right) + \theta \Delta \ln\left(L_i\right) + \pi \Delta\left(H_i\right) + X_{3i} b_3 + u_{3i} \tag{6a}$$

$$\Delta \ln q_i = \Delta \ln \frac{Y_i}{L_i} = \varphi_2 nst_i^* + \delta \Delta \ln\left(\frac{K_i}{L_i}\right) + \theta \Delta \ln\left(L_i\right) + \pi \Delta\left(H_i\right) + X_{3i} b_3 + u_{3i} \tag{6b}$$

To assess the robustness of the results, the model is replicated on a subsample consisting of firms that used TETS, compared to a control group of non-users with similar observable characteristics. The matching procedure applies PSM, which estimates the probability of using TETS based on observable firm attributes. This method is commonly used to approximate causal inference, as applied in Gallego and Gutiérrez (2017) to evaluate the impact of quality certification on labor productivity, and the results are «as good as randomization» (Heinrich et al., 2010).

The propensity score ($P(x_0)$) is estimated as the probability of using TETS (gst), conditional on observable characteristics (x_0) (Becker and Ichino, 2002). Next, a balance test is performed to ensure that variable differences are not statistically significant within each distribution block.

$$P\left(x_0\right) = \Pr\left(gst = 1 \mid x_0\right) \tag{7}$$

Firms are matched using Nearest-Neighbor Matching (NNM), selecting a set of control firms ($c(i)$) with the closest propensity scores within a pre-defined threshold (ψ). Each treated firm is matched with four control firms, using weighting $w_1(i, j)$ to construct the comparison group:

$$c(\ i\ ) = \left\{ j \in D = 0 \ \| \ P_i\left(x_0\right) - P_j\left(x_0\right) \| \leq \psi \right\} \tag{8}$$

Additionally, Kernel Matching is applied to assign weighted averages to both treated and control firms, minimizing sample loss. The weighting function follows:

$$w_2\left(i,j\right) = \frac{K\left(\dfrac{P_j\left(x_0\right) - P_i\left(x_0\right)}{a_n}\right)}{\Sigma_{kec}\, K\left(\dfrac{P_j\left(x_0\right) - P_i\left(x_0\right)}{a_n}\right)} \tag{9}$$

where $w_2(i, j)$ represents the weight and K(.) is the Kernel function.

Once the subsample is defined, the CDM model is replicated, applying the associated weights ($w_2(i, j)$) to each firm identified as a counterfactual, and the results are compared.

To test H2, an additional variable indicating whether the firm invested in internal R&D is included in the innovation equation (Equations 4a and 4b), and its complementarity with TETS usage is assessed. Similarly, complementarity is evaluated with respect to other innovation variables, such as engineering, design, and other creative activities; marketing; intellectual property; software and database development or acquisition; and the acquisition or rental of capital goods. This assessment is performed both at the individual activity level and jointly within a single equation. Following the model proposed by Lopez (2024), adapted for probability models, Equations 4a and 4b are reconfigured as follows:

Individual level:

$$pst_i = \alpha_k rst_i^* + \beta_k act_{ji} + \delta_k\left(rst_i^* \times act_{ji}\right) + X_{2i} b_k + u_{ki} \tag{10a}$$

$$nst_i = \alpha_k rst_i^* + \beta_k act_{ji} + \delta_k\left(rst_i^* \times act_{ji}\right) + X_{2i} b_k + v_{ki} \tag{10b}$$

Jointly:

$$pst_i = \alpha_k rst_i^* + \Sigma_{j=1}^{J}\left(\beta_{jk} act_{ji}\right) + \Sigma_{j=1}^{J} \delta_k \left(rst_i^* \times act_{ji}\right) + X_{2i} b_k + u_{ki} \quad (11a)$$

$$nst_i = \alpha_k rst_i^* + \Sigma_{j=1}^{J}\left(\beta_{jk} act_{ji}\right) + \Sigma_{j=1}^{J} \delta_k \left(rst_i^* \times act_{ji}\right) + X_{2i} b_k + v_{ki} \quad (11b)$$

Where act_{ji} represents the investment (or decision to invest) in activity j by firm i, and the term $rst^*_i \times act_i$ capture s the interaction between TETS investment and activity j.

To assess complementarity, we evaluate the statistical significance of the interaction parameter δ_k. Since Equation (10a/11a) is non-linear (Probit), the interaction effect is not automatically given by the coefficient δ_k. Therefore, we calculate the marginal effects (discrete differences) of the interaction term to ensure accurate interpretation of complementarity.

Finally, to assess the cost-effectiveness of investing in R&D versus TETS, the dose-response function is estimated using the GPS method. This technique evaluates the impact of a treatment when it is continuous rather than binary or discrete, allowing for an analysis of treatment intensity (Bia & Mattei, 2008). The core idea is to obtain a potential outcome (Y) for each potential treatment level (t). Thus, the set of potential outcomes for a range of treatments (τ) is defined as $\{Y_i(t)\}_{t\in\tau}$. This methodology consists of three steps:

- In the first stage, the GPS score $R = r(T, X)$ is estimated as the conditional density of the treatment level T given the covariates X.
- In the second stage, the expected conditional outcome parameter is obtained: $\beta(t, r) = E(Y \mid T = t, R = r)$.
- In the third stage, the dose-response function is estimated as $\mu(t) = E[\beta(t, r(t, X))]$, $t \in \tau$

The goal is to estimate the percentage change in sales for each percentage change in R&D or ETTS expenditure. Confidence intervals are constructed using Bootstrap. Dai & Cheng (2015) apply this methodology to investigate the impact of public subsidies on R&D investment in Chinese manufacturing firms.

3.4. Descriptive statistics

Table 1 shows the main descriptive statistics of the variables used in the models. Between 2015 and 2016, 12.7% of firms used TETS. A total of 30% introduced a product innovation, with sales from innovative products averaging 14.3% of total sales. Sales per worker – in Peruvian soles (PEN) – declined, from PEN 481,000 in 2015 to PEN 444,000 in 2017.

On average, firms had 18.2 years of operation and employed 227 workers. Innovation-related linkages were weak, with the highest being firm-to-firm collaborations (4%). Most firms operated in diversified markets (34% in highly competitive industries and 53% in unconcentrated industries) with low market shares. Physical capital per worker increased by 56%.

Table 1. Descriptive statistics of the variables

Variable	Mean	Standard Deviation	Minimun	Maximun
Dependent variables				
Invested in TETS 2015-2016	0.13	0.333	0	1
Invested in internal R&D 2015-2016	0.12	0.323	0	1
Product innovation	0.3	0.46	0	1
Percentage of sales from innovative products 2017	14.28	30.394	0	100
Difference in sales per worker	-0.09	0.568	-5	3.3
Independent variables				
Firm age	18.23	14.761	1	108
Foreign capital	0.16	0.363	0	1
Employees in 2015	227.65	740.773	1	16578
Exporter in 2015	0.37	0.482	0	1
Qualified workers in 2015	0.26	0.257	0	1
Financial constraints	0.46	0.498	0	1
Linkage (companies)	0.04	0.191	0	1
Linkage (consulting firms)	0.02	0.135	0	1
Linkage (institutes and universities)	0.02	0.123	0	1
Market share	0.02	0.087	0	1
Technology obstacles	0.32	0.466	0	1
Demand obstacles	0.59	0.492	0	1
Risk perception	0.43	0.495	0	1
Accessed R&D&I program	0.03	0.169	0	1
Concentration (highly competitive)	0.34	0.475	0	1
Concentration (not concentrated)	0.53	0.499	0	1
Concentration (moderate)	0.11	0.308	0	1
Manufacturing/low technology	0.44	0.496	0	1
Manufacturing/medium technology	0.14	0.346	0	1
Manufacturing/medium-high technology	0.13	0.337	0	1
Knowledge-intensive services (KIS)	0.29	0.454	0	1
Business group	0.18	0.386	0	1

Variable	Mean	Standard Deviation	Minimun	Maximun
Main product ratio 2015	80.38	25.894	0	100
Acquired or developed software	0.13	0.334	0	1
Invested in R&D in 2015	0.1	0.304	0	1
SME in 2015	0.36	0.479	0	1
Intellectual property	0.04	0.201	0	1
Difference in capital per worker	0.56	4.446	-16.2	17.3
Difference in workers	0.04	0.378	-4.1	3.4
Difference in % of skills	0.01	0.068	-0.4	0.8

Note: Statistics based on the sample of 2,032 companies.
Source: National Innovation Survey (NIS) 2018.

4. Results

4.1. Decision to invest in tets and investment intensity

The first stage of the CDM model examines firms' decision to use TETS and investment intensity. The estimated rho ($\hat{\rho}$) is statistically significant, indicating selection bias, which has been addressed. The results are shown in Table 2, the third column corresponds to the results of the decision to invest in TETS, while the second one refers to the intensity of spending, both cases referring to the total sample. Columns 4 to 7 repeat both regressions for the samples using the Kernel and Nearest Neighbor matching methods.

The number of employees has a positive effect on the decision to invest but a negative effect on investment intensity, consistent with findings for Peru (García, 2022; Tello, 2020). Market concentration is not significant in either stage, except for moderate concentration, which is significant for investment decisions. Firms may pursue these investments for various reasons (Lipczynski et al., 2017): while large firms have greater resources, they may also face bureaucratic barriers or exhibit a complacent attitude. In contrast, firms in competitive markets may invest in TETS to enhance their competitiveness.

The share of qualified workers has a positive effect, in line with Lööf and Heshmati (2006) and Ramadani et al. (2019). Technological barriers influence investment decisions, as firms rely on external sources to acquire unavailable technologies. Market constraints, particularly demand-side challenges, may also encourage firms to innovate—especially those following a defensive R&D strategy (Lipczynski et al., 2017).

For investment intensity, firm age exhibits a quadratic relationship: positive in early years but declining over time. TETS programs typically target smaller firms and focus on transferring existing technology. Initially, these services are essential, but as firms establish themselves and develop internal expertise, their reliance on TETS declines.

Linkages with other entities are not significant, although belonging to a business group has a positive effect. This supports Díaz and Kuramoto (2010), who note that Peru's National Innovation System remains underdeveloped, with weak coordination between industry and scientific institutions.

For the matched sample, all variables in the first stage of the model are not significant, as expected, since they were used for matching. However, $\hat{\rho}$ still indicates selection bias.

For investment intensity, coefficients for firm age, employment, and share of qualified workers are similar in sign and magnitude to those in the full sample, making them the only statistically significant variables. Physical capital per worker is not significant in this case.

Table 2. Estimation of the first stage, decision and intensity of spending on technology extension and transfer services

Variables	Total sample		Matched sample (NNM)		Matched sample (Kernel)	
	log(spending on TETS)	decision to invest in TETS	log(spending on TETS)	decision to invest in TETS	log(spending on TETS)	decision to invest in TETS
log(firm age)	7.729*** (2.723)	0.065 (0.051)	7.416*** (2.753)	0.042 (0.075)	7.087** (2.808)	0.0154 (0.683)
log(firm age)^2	-3.913*** (1.416)		-3.787*** (1.434)		-3.623** (1.461)	
log(employees 2015)	-0.365*** (0.107)	0.096*** (0.028)	-0.471*** (0.105)	0.053 (0.044)	-0.457*** (0.104)	0.062 (0.041)
linkage (companies)	-0.014 (0.290)		-0.018 (0.296)		-0.021 (0.295)	
linkage (consulting firms)	0.375 (0.458)		0.384 (0.453)		0.337 (0.454)	
linkage (institutes and universities)	0.448 (0.549)		0.447 (0.529)		0.434 (0.530)	
linkage (innovation centers and government)	0.419 (0.573)		0.538 (0.599)		0.548 (0.598)	
qualified workers	2.710*** (0.702)	0.477*** (0.173)	1.792*** (0.657)	-0.134 (0.267)	1.952*** (0.673)	0.009 (0.261)
exporting company 2015	0.197 (0.307)	0.205** (0.085)	-0.318 (0.285)	-0.142 (0.126)	-0.333 (0.278)	-0.151 (0.115)
foreign capital	0.418 (0.358)	0.116 (0.101)	0.261 (0.340)	0.0541 (0.149)	0.228 (0.333)	0.0383 (0.139)
not concentrated	-0.515* (0.291)	-0.112 (0.104)	-0.314 (0.286)	-0.009 (0.142)	-0.376 (0.274)	-0.058 (0.128)
moderate concentration	0.797** (0.406)	0.032 (0.139)	0.811** (0.401)	0.021 (0.188)	0.826** (0.390)	0.038 (0.171)

Variables	Total sample		Matched sample (NNM)		Matched sample (Kernel)	
	log(spending on TETS)	decision to invest in TETS	log(spending on TETS)	decision to invest in TETS	log(spending on TETS)	decision to invest in TETS
high concentration	-0.393 (0.722)	-0.127 (0.249)	-0.218 (0.739)	-0.158 (0.341)	-0.205 (0.717)	-0.105 (0.322)
main product ratio 2015	-0.004 (0.005)	-0.002 (0.001)	-0.002 (0.005)	-0.001 (0.002)	-0.002 (0.004)	-0.001 (0.002)
government funding	0.152 (0.560)		0.095 (0.563)		0.099 (0.565)	
financial constraints	0.195 (0.260)	0.064 (0.086)	0.085 (0.257)	0.023 (0.118)	0.071 (0.253)	-0.013 (0.110)
risk perception	0.231 (0.291)	0.0458 (0.085)	0.065 (0.286)	-0.087 (0.121)	0.117 (0.281)	-0.062 (0.112)
log(capital 2015)	0.063* (0.033)	0.029*** (0.009)	0.023 (0.032)	0.010 (0.014)	0.020 (0.031)	0.007 (0.012)
technology obstacles	0.258 (0.300)	0.208** (0.086)	0.098 (0.293)	0.164 (0.124)	0.064 (0.285)	0.117 (0.115)
demand obstacles	0.244 (0.310)	0.185** (0.090)	-0.112 (0.312)	-0.018 (0.133)	-0.074 (0.304)	0.026 (0.122)
business group	0.773*** (0.278)	0.118 (0.093)	0.454 (0.279)	-0.083 (0.134)	0.466* (0.274)	-0.109 (0.125)
$\hat{\rho}$		1.358*** (0.216)		1.178*** (0.230)		1.165*** (0.228)
Constant	2.702** (1.306)	-2.017*** (0.248)	6.207*** (0.964)	-0.198 (0.372)	6.143*** (0.952)	-0.162 (0.345)
Observations	2,032	2,032	781	781	1,856	1,856

Note: Controlled for industry type and geographic factors.
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: National Innovation Survey (NIS) 2018.

4.2. Innovation outcomes

Table 3 shows the results of the innovation equation (Eq. 4). The analysis considers two innovation variables: product innovation and the share of total sales from innovative products. In both cases, the predicted TETS investment intensity variable is positive and significant. Similar findings are reported by Ramadani et al. (2019) and Martin and Nguyen-Thi (2015), who use external knowledge acquisition as a proxy for innovation activities, as well as by Na (2021) in the context of workforce training.

Some variables are also positively significant, including the number of employees, consistent with other research (Edeh and Acedo, 2021; Ramadani et al., 2019); software development/acquisition, a proxy for ICT use, which plays a key role in innovation processes, (Martin and Nguyen-Thi, 2015) intellectual property protection (Ramadani et al., 2019); and SME status. Regarding the latter, smaller firms may find it easier to introduce new products more quickly due to fewer bureaucratic barriers (Lipczynski et al., 2017). Additionally, in Peru, SMEs benefit from more flexible labor and tax regulations and are prioritized in public R&D&I subsidy programs.

For product innovation, demand-side constraints prove relevant, suggesting that firms innovate as a defensive strategy in response to market restrictions. Access to government R&D&I programs also has a positive effect, aligning with Edeh and Acedo (2021). The coefficient for the main product's sales share is negative, indicating that more diversified firms are more likely to engage in innovation. However, this variable is not significant for the second innovation measure, implying that while it affects innovation achievement, it does not necessarily translate into commercial success.

For the matched sample, product innovation coefficients remain significant and similar in magnitude. Other variables show consistent patterns, except for software development, access to R&D&I programs, and the main product's sales ratio. Regarding the share of sales from innovative products, TETS investment intensity remains significant, but some discrepancies arise across matching methods. Under NNM, intellectual property protection, foreign capital participation, and software acquisition are not significant. In contrast, under Kernel Matching, risk perception is not significant, whereas software development and foreign capital participation are.

Table 3. Estimation of the second stage, innovation outcomes

Variables	Total sample		Matched sample (NNM)		Matched sample (Kernel)	
	log(spending on TETS)	decision to invest in TETS	log(spending on TETS)	decision to invest in TETS	log(spending on TETS)	decision to invest in TETS
predicted spending on SETT	0.036*** (0.012)	2.208*** (0.781)	0.123*** (0.039)	7.384** (3.905)	0.101*** (0.034)	6.880** (2.854)
log(employees 2015)	0.033*** (0.009)	1.624** (0.648)	0.086*** (0.026)	6.162*** (2.110)	0.071*** (0.023)	4.999*** (1.894)
technology obstacles	0.004 (0.022)	2.005 (1.560)	0.042 (0.044)	6.142* (3.634)	0.035 (0.040)	6.225* (3.429)
demand obstacles	0.069*** (0.022)	1.930 (1.545)	0.127*** (0.046)	2.558 (3.781)	0.115*** (0.041)	2.265 (3.540)
foreign capital	-0.043 (0.029)	-4.027** (1.971)	-0.068 (0.057)	-6.252 (4.350)	-0.064 (0.051)	-6.649* (3.994)
risk perception	-0.040* (0.021)	-2.748* (1.480)	-0.082* (0.043)	-6.161* (3.574)	-0.067* (0.039)	-5.185 (3.359)
not concentrated	0.003 (0.026)	0.071 (1.824)	-0.011 (0.054)	-0.363 (4.818)	-0.009 (0.049)	0.541 (4.426)

Variables	Total sample		Matched sample (NNM)		Matched sample (Kernel)	
	log(spending on TETS)	decision to invest in TETS	log(spending on TETS)	decision to invest in TETS	log(spending on TETS)	decision to invest in TETS
moderate concentration	0.004 (0.033)	0.875 (0.646)	-0.082 (0.077)	-4.664 (6.835)	-0.041 (0.067)	-3.147 (6.288)
high concentration	0.074 (0.071)	4.700 (5.431)	0.086 (0.110)	0.581 (11.190)	0.139 (0.091)	4.876 (10.730)
acquired or developed software	0.173*** (0.027)	14.660*** (2.657)	0.040 (0.044)	5.541 (3.728)	0.033 (0.040)	6.520* (3.569)
accessed R&D&I program	0.216*** (0.064)	6.903 (4.950)	0.057 (0.088)	-4.574 (6.447)	0.049 (0.082)	-4.151 (6.618)
invested in R&D in 2015	0.284*** (0.031)	13.74*** (3.025)	0.167*** (0.045)	6.010 (3.843)	0.163*** (0.043)	6.121 (3.755)
main product ratio 2015	-0.001*** (0.000)	-0.043 (0.028)	-0.001 (0.001)	-0.030 (0.063)	-0.001 (0.001)	-0.024 (0.062)
SME	0.079*** (0.027)	5.021** (2.049)	0.171*** (0.058)	17.740*** (5.331)	0.126** (0.051)	12.830*** (4.951)
intellectual property	0.245*** (0.057)	7.759* (4.468)	0.124* (0.071)	-2.576 (4.875)	0.180*** (0.064)	1.037 (4.810)
Constant		2.575 (5.336)		-29.150 (23.790)		-21.170 (21.940)
Observations	2,032	2,032	781	781	1,856	1,856
R^2	0.161	0.091	0.103	0.070	0.102	0.058

Notes: Controlled for industry type and geographic factors. The probit model shows marginal effects and MacFadden R^2. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: National Innovation Survey (NIS) 2018.

4.3. Productivity outcomes

The primary finding is the positive significance of predicted innovation, a result consistent with Lööf and Heshmati (2006), who also measure differences in sales per worker. Jarmin (1999) and Lipscomb et al. (2018) directly assess the impact of technology extension programs on productivity and find positive effects. As shown in columns 2 and 3 of Table 4

Regarding production factors, physical capital exhibits a positive and significant effect, aligning with previous literature. However, labor is significant but negatively correlated – a finding similar to Edeh and Acedo (2021) for process and marketing innovation. Crépon et al (1998), Lööf and Heshmati (2006), and Tello (2020) do not report significance for this variable. The share of employees with higher education is only significant at the 10% level. Financial constraints also emerge as a relevant factor.

For the matched sample (columns 3 to 6 of Table 4), innovation variables remain significant only for the sales share measure, with coefficients similar to those found in the full sample. Among production factors, capital and the number of employees remain significant, whereas skilled labor is not. The country's high occupational mismatch may explain these results. Compared to the previous stage, the matched sample shows a better model fit, particularly under NNM.

Table 4. Estimation of Firm Performance

Variables	Total sample		Matched sample (NNM)		Matched sample (Kernel)	
	log(spending on TETS)	decision to invest in TETS	log(spending on TETS)	decision to invest in TETS	log(spending on TETS)	decision to invest in TETS
Predicted innovation	0.222*** (0.052)	0.005*** (0.001)	0.086 (0.116)	0.004* (0.002)	0.088 (0.105)	0.004** (0.002)
Difference in log capital per worker	0.015*** (0.003)	0.015*** (0.004)	0.016*** (0.006)	0.016*** (0.006)	0.016*** (0.005)	0.016*** (0.005)
Difference in log of labor	-0.427*** (0.092)	-0.428*** (0.091)	-0.538*** (0.072)	-0.537*** (0.071)	-0.525*** (0.070)	-0.527*** (0.068)
Difference in % of qualified workers	0.437* (0.264)	0.444* (0.264)	0.179 (0.422)	0.190 (0.418)	0.359 (0.363)	0.369 (0.360)
Log seniority	-0.026 (0.018)	-0.026 (0.018)	0.002 (0.025)	0.005 (0.025)	-0.015 (0.025)	-0.013 (0.025)
Financial constraints	-0.042* (0.024)	-0.044* (0.024)	-0.085** (0.036)	-0.097*** (0.036)	-0.064* (0.036)	-0.075** (0.036)
Constant	-0.090 (0.069)	-0.129* (0.071)	-0.067 (0.129)	-0.197 (0.162)	-0.033 (0.115)	-0.163 (0.145)
Observations	2,032	2,032	781	781	1,856	1,856
R^2	0.104	0.104	0.164	0.169	0.153	0.157

Notes: Controlled by industry type and geographic factors.
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: NIS 2018.

4.4. Comparison between models using tets and others innovation activities

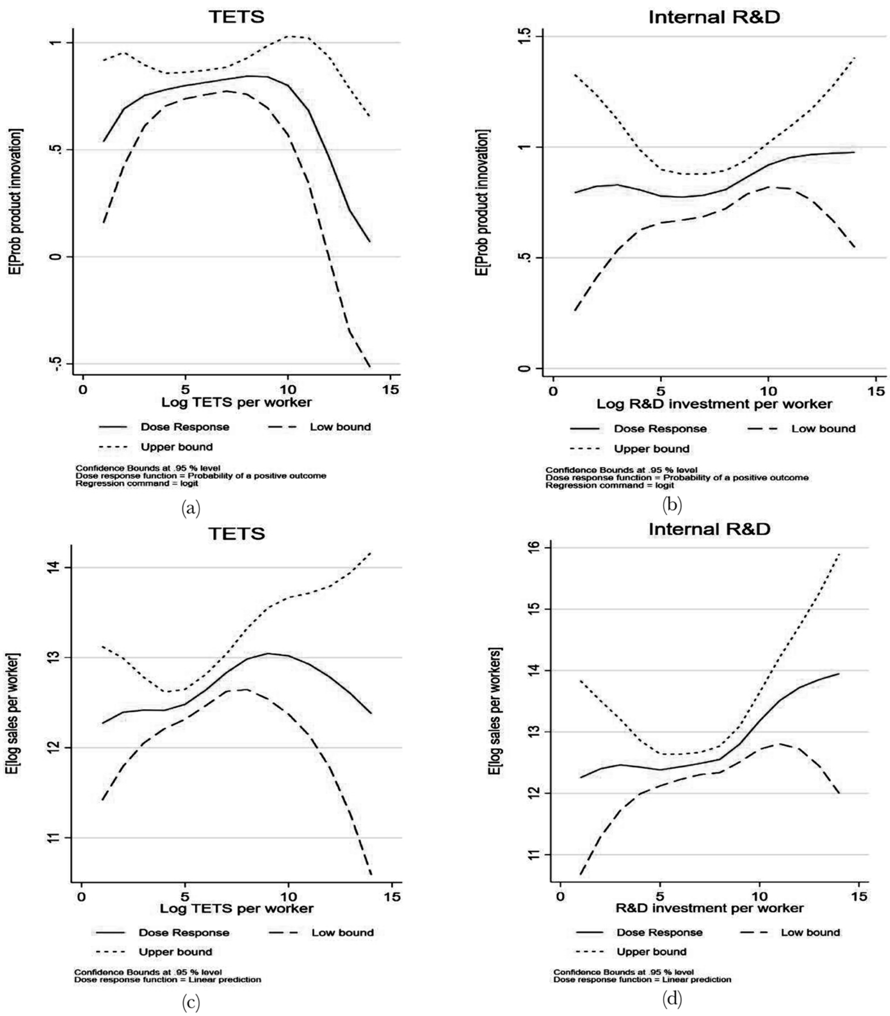
This section applies Equations 10a, 10b, and 11a, 11b. Specifically, independent models are estimated, each including one of the following variables: i) internal R&D; ii) engineering, design, and other creative activities; iii) marketing and brand value; iv) intellectual property; v) software and database development or acquisition; and vi) acquisition or rental of capital goods (including hardware).

The results, presented in Annex 2, indicate that all innovation activity variables were individually statistically significant. Notably, investment in engineering, design, and other creative activities exhibited the highest marginal effect on the probability of innovation across both outcome variables considered. However, regarding the interaction with TETS investment intensity, a significant and positive relationship was found only for product innovation in the context of software and database development or acquisition. Conversely, the interaction term was significant but negative for intellectual property. This finding suggests a potential complementarity between ICT usage and technology extension and transfer services. In this context, García (2022) also identified positive effects of software acquisition on productivity.

The dose-response function, estimated using the GPS method, quantifies the marginal effect of both types of investment on innovation and labor productivity outcomes (see Figure 2). Examining the relationship between the probability of product innovation and investment in TETS and internal R&D, the findings first highlight a rapid increase in innovation likelihood at low levels of TETS investment, followed by a gradual decline, plateauing around PEN 8,000 per worker, after which it begins to decrease. This pattern reflects the quadratic relationship in external knowledge acquisition documented by previous studies (Carboni and Medda, 2021; Hottenrott and Lopes-Bento, 2016). Excessive investment in TETS may become counterproductive by increasing coordination, management, and oversight costs while potentially constraining a firm's ability to develop internal knowledge. In contrast, internal R&D – although showing a lower slope in certain segments – maintains a consistently upward trend.

The effect of investment on sales growth also reveals a positive relationship between TETS spending and increased sales, but only at moderate investment levels. Similar to the innovation probability curve, the effect diminishes around PEN 8,000 per worker. For internal R&D, however, once this investment threshold is exceeded, the sales impact accelerates significantly.

Figure 2. Dose-Response Function of Expenditure on TETS and Internal R&D



Source: NIS 2018.

5. Conclusions

Innovation is a key driver of firm productivity. However, investing in internal R&D can be prohibitively expensive due to the substantial financial commitment and associated risks. As a result, many firms choose to acquire knowledge externally, which allows them to share risk with other actors, foster technology transfer, and enhance their commercial and organizational capabilities. In EMEs, external knowledge acquisition also facilitates access to proven technologies in a shorter timeframe.

The decision to invest in TETS is influenced by firm size, human capital, and market constraints. This finding suggests that firms adopt a defensive innovation strategy to maintain competitiveness. In contrast, investing in internal R&D is associated with factors such as market structure, business linkages, and product diversification – suggesting an offensive innovation strategy aimed at market expansion.

Regarding TETS investment intensity, firm age plays a relevant role, though the relationship is nonlinear. Initially, firms that invest in TETS benefit from greater experience, improved internal capabilities, and enhanced access to external knowledge providers (Chen et al., 2015). However, as firms gain expertise, they may transition away from TETS, opting instead to develop in-house knowledge.

Firm linkages were not found to be significant in explaining TETS investment intensity, possibly due to the weak integration and coordination within the National Innovation System (Díaz and Kuramoto, 2010). This underutilization of collaborative innovation opportunities could be a missed opportunity, particularly in the context of Industry 4.0, where rapidly evolving market needs demand open innovation strategies (Alkhazaleh et al., 2022). Policy should encourage firms requiring high investment levels to begin developing in-house knowledge, thereby enabling them to sustain the increasing investment trajectory offered by internal R&D.

The results confirm that TETS investment significantly contributes to innovation, even when controlling for selection bias. Other variables positively associated with innovation include firm size, intellectual property expenditure, and R&D investment. Additionally, the inverse relationship between risk perception and export status with innovation suggests that firms with lower risk tolerance may be more cautious in pursuing innovation.

Innovation was also found to have a significant impact on sales performance. However, in the matched sample, the only significant effect was observed for the share of sales from innovative products. This implies that while the direct relationship between innovation and labor productivity remains unclear, successful innovations – measured through their contribution to sales – are clearly linked to better firm performance. In this regard, the sales share of innovative products is widely recognized as a key indicator of innovation success (Carboni and Medda, 2021).

The dose-response function indicates that TETS investments yield positive effects at moderate levels; however, as spending increases, the growth rate turns negative. This suggests a quadratic relationship between external knowledge acquisition and firm performance. This pattern does not hold for internal R&D, where the trend remains consistently positive. Policies should be designed to bridge the investment gap that firms cannot sustain independently, whether through direct subsidies or subsidized service pricing. This would ensure that firms reach the 'optimal' investment level before the effect reverses.

TETS investment represents a viable strategy for firms facing multiple constraints in accumulating and transforming knowledge into innovation. This is particularly relevant for younger firms seeking to invest cautiously and at lower risk.

More broadly, investment in innovation activities emerges as a viable strategy for enhancing firm performance. In the short term, both TETS and internal R&D yield similar results, with both serving as strong predictors of innovation. This allows firms to pursue innovation strategies without bearing the full risks associated with in-house knowledge development.

The impact of TETS would be significantly enhanced if implemented within an environment characterized by strong linkages among innovation actors. Consequently, the development of policies aimed at strengthening the National Innovation System and fostering open innovation is recommended. This entails the institutional strengthening of public organizations, such as CITEs, universities, and research centers. Innovation policies must incorporate a component that ensures the monitoring and evaluation of interventions. This is vital for distinguishing policies that are truly cost-effective and achieve tangible results in firm performance.

Finally, this study has certain limitations. The analysis is constrained to a three-year period due to the scope of available data in the ENI, preventing an assessment of long-term effects. Additionally, the measurement of TETS is limited to external R&D and innovation-related training, as these are the only activities explicitly identified as externally acquired in the dataset. Other relevant services, such as engineering and design, could not be distinguished between internal and external investment. Furthermore, data constraints prevented the inclusion of more comprehensive productivity indicators, notably TFP.

Future research should prioritize the use of longitudinal (panel) datasets or the forthcoming edition of the ENI to assess the persistence of TETS effects on innovation and productivity beyond the short term. In particular, it is crucial to compare the growth trajectory of internal R&D – which exhibits a consistently upward path – against that of TETS, which follows a quadratic pattern. Furthermore, the complementarities between TETS and the adoption of digital technologies (ICT/Software) warrant deeper investigation, extending the exploratory analysis conducted in this study. This would allow for the determination of whether the returns on external knowledge services are amplified when firms have already reached a specific digitization threshold.

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Annex 1: Variables Used in the CDM Models

Variable	Name	Type	Definition
Dependent Variables			
Decision to invest in TETS	st1516	Qualitative (Dummy)	1 if the company invested in TETS, 0 if it did not. For the years 2015 and 2016.
Investment in TETS per worker	lstrab_1516	Quantitative	Logarithm of the amount of investment in TETS per worker.
Product innovation results	inn_prod	Qualitative (Dummy)	1 if the company carried out product innovations, 0 if it did not.
Percentage of innovations on sales	pvent_inn	Quantitative	Percentage of sales corresponding to innovations in 2017.
Sales per worker	lventrab_17	Quantitative	Logarithm of net sales per worker in the year 2017.
Difference in sales per worker	d_lventast	Quantitative	Difference in the logarithm of net sales between 2015 and 2017.
Explanatory Variables			
Market Participation			
Market share	cuota	Quantitative	Ratio between the company's total sales and the total sales of the sector by macro-region.
Market concentration	nivhhi	Qualitative	1 for diversified industry; 2 for moderate concentration; 3 for concentrated industry. Based on Herfindahl-Hirschman Index (HHI) values.
Diversification	princ	Quantitative	Percentage of sales from the main product relative to total sales in 2015.
Experience	lantig	Quantitative	Years of company operation from its start until the survey date.
Firm Size			
Firm size	sme_15	Qualitative	1 for small and medium-sized enterprises; 0 for large enterprises.
Workers	lemp_15	Quantitative	Logarithm of the number of workers in 2015.

Variable	Name	Type	Definition
Sectoral Effects			
Economic sector	act_econ	Qualitative	1 for low-tech industry; 2 for medium-tech industry; 3 for medium-high-tech industry; 4 for knowledge-intensive services (According to UNIDO classification).
Region	lima	Qualitative	1 for Lima and Callao; 0 for other regions.
Demand Pull			
Demand pull	dempull	Qualitative (Dummy)	1 for medium to high obstacles due to uncertainty regarding demand for innovative goods and services, markets dominated by established firms, and small market size; 0 otherwise.
Risk aversion	riesgo	Qualitative (Dummy)	1 for perception of economic risk; 0 otherwise.
Participation in international markets	emp_exp15	Qualitative (Dummy)	1 if the company exported during the analysis period; 0 otherwise.
Sectoral Technological Level			
Intellectual property	propint	Qualitative	1 if the company invested in intellectual property; 0 otherwise.
Participation in STI support programs	programa	Qualitative (Dummy)	1 if the company participated in any program; 0 otherwise.
Financing obstacles	rfin	Qualitative (Dummy)	1 if the company reported obstacles to financing innovation activities; 0 otherwise.
Technology push	tecpush	Qualitative (Dummy)	1 if the company faced limited technological opportunities; 0 otherwise.
Foreign capital	kext_15	Qualitative (Dummy)	1 if the company received foreign capital in 2015; 0 otherwise.
Active linkages	vinc*	Qualitative	1 with related companies; 2 with specialized firms; 3 with research centers and universities; 4 with innovation centers and government.

Variable	Name	Type	Definition
Physical Capital Intensity			
Capital investment	lcaptrab_15	Quantitative	Logarithm of capital investment in 2015.
Variation in capital investment	dlcap_1517	Quantitative	Difference in the logarithm of capital investment between 2015 and 2017.
Workforce Quality			
Skilled personnel	skill_15	Quantitative	Percentage of workers with higher education in 2015.

Annex 2: Marginal effects of innovation activities

Variables	Individual level				Jointly	
	Log TETS expenditure	Innovation activity	Interaction (TETS × Activity)	R-squared	Innovation activity	Interaction (TETS × Activity)
Internal R&D						
Product innovation	0.143***	1.375***	-0.093	0.129	0.823***	-0.080
Innovation sales ratio	2.463***	19.41***	-0.404	0.062	7.397	0.225
Engineering, design, and other creative activities						
Product innovation	0.139***	1.413***	0.049	0.17	1.132***	0.017
Innovation sales ratio	2.460***	21.66***	0.355	0.083	15.27**	-0.277
Marketing and brand value						
Product innovation	0.170***	1.184***	-0.051	0.113	0.778***	-0.078
Innovation sales ratio	2.942***	14.39**	0.204	0.047	2.742	0.815
Intellectual property (IP)						
Product innovation	0.171***	1.574***	-0.167	0.106	0.644	-0.012
Innovation sales ratio	3.179***	29.21***	-5.586*	0.047	14.56	-4.923
Software and database development or acquisition						
Product innovation	0.151***	0.457***	0.147**	0.113	0.0347	0.156*
Innovation sales ratio	2.621***	12.90***	2.270	0.071	6.972	1.791
Acquisition or rental of capital goods (includes hardware)						
Product innovation	0.154***	0.809***	0.061	0.129	0.581***	0.030
Innovation sales ratio	2.579***	14.19***	1.391	0.070	7.624	1.185

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Economic Growth, AI Adoption and Human Capital Across the OECD: Evidence from a Panel ARDL Model

Crescimento Económico, Adoção de IA e Capital Humano nos Países da OCDE: Evidência a partir de um modelo ARDL de painel

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ABSTRACT

Technological progress is a key driver of long-term growth and increases in standards of living across generations, but its benefits often materialise with delay due to adjustment costs and the need for complementary investments. This study examines these dynamics for artificial intelligence (AI), whose rapid diffusion has raised expectations about its economic impact. As with previous waves of technological progress and innovation, there are also important concerns on how work will be shaped by the proliferation of AI as it may potentially benefit certain types of human capital. Using a panel ARDL model for 35 OECD countries from 1995 to 2017, we estimate the short- and long-run effects of AI adoption on growth and living standards. The ARDL framework captures the gradual adjustment process and allows us to incorporate human capital by interacting it with AI, assessing whether the benefits of AI differ across skill levels. Our preferred results, based on patents data and first differenced GMM, suggest that AI adoption already contributes to short-run growth and leads to long run improvements in standards of living, although these results are not supported in all contexts. Regarding the role of human capital, our aggregate data provides no evidence that AI benefits any particular group of workers, neither highly educated

nor less-educated ones. Our research is limited by the current state of AI technology, which is advancing rapidly, and proxies available; therefore, the validity of our present, optimistic findings must be continually re-evaluated.
Keywords: *Artificial Intelligence, Technological Progress, Human Capital, Economic Growth, OECD, Panel ARDL.*

JEL Classification: C33; O33; O47

RESUMO

O progresso tecnológico é um dos principais motores do crescimento de longo prazo e do aumento dos padrões de vida ao longo das gerações, mas os seus benefícios tendem a materializar-se com atraso devido a custos de ajustamento e à necessidade de investimentos complementares. Este estudo analisa estas dinâmicas no caso da inteligência artificial (IA), cuja rápida difusão elevou as expectativas quanto ao seu impacto económico. Tal como em vagas anteriores de progresso tecnológico e inovação, existem também importantes preocupações sobre a forma como o emprego será moldado pela proliferação da IA, uma vez que esta poderá potencialmente beneficiar certos tipos de capital humano. Utilizando um modelo ARDL em painel para 35 países da OCDE entre 1995 e 2017, estimamos os efeitos de curto e longo prazo da adoção de IA no crescimento e nos padrões de vida. O enquadramento ARDL capta o processo gradual de ajustamento e permite incorporar o capital humano mediante a sua interação com a IA, avaliando se os benefícios desta diferem consoante os níveis de qualificação. Os nossos resultados preferidos, baseados em dados de patentes e no método GMM em primeiras diferenças, sugerem que a adoção de IA já contribui para o crescimento de curto prazo e conduz a melhorias de longo prazo nos padrões de vida, embora estes resultados não se verifiquem em todos os contextos. Quanto ao papel do capital humano, os nossos dados agregados não fornecem evidência de que a IA beneficie qualquer grupo específico de trabalhadores, sejam eles mais ou menos qualificados. A nossa investigação é limitada pelo estado atual da tecnologia de IA, que evolui rapidamente, e pelas proxies disponíveis; por isso, a validade das nossas conclusões, atualmente otimistas, deve ser continuamente reavaliada.

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Economic Growth, AI Adoption and Human Capital Across the OECD: Evidence from a Panel ARDL Model

1. Introduction

Artificial intelligence (AI) stands out as a key driver of transformation, OECD (2019), Briggs and Kodnani (2023), Lagarde (2025). Economically, AI is reshaping how businesses operate, with the potential to boost productivity and efficiency, thereby fostering economic growth and enhancing the well-being of present and future generations. As AI continues to evolve, it becomes increasingly important to understand its impact on economic growth and standards of living, Trabelsi (2024). The implications of the widespread adoption of AI for business performance and economic growth are also tightly linked with human capital. While some workers may be negatively affected by AI technologies, others stand to benefit, largely depending on whether AI substitutes or complements their particular skill sets, see e.g. Autor (2015), Acemoglu & Restrepo (2019), Brynjolfsson, Li, & Raymond (2025), Bughin (2025).

Economic growth, i.e. the sustained increase in the capacity of production of goods and services by an economy is fundamental to ensuring the continuous improvement of living standards across generations. While growth can stem from greater availability of inputs such as physical and human capital, its most significant drivers are gains in efficiency and productivity in the use of these resources. Endogenous growth models identify technological progress and productivity improvements as the main source of growth, Romer (1986), Romer (1990), Jones (1995), but Solow (1956) already concluded that improvements in technology, considered exogenous, are a necessary condition for sustained growth. Indeed, since the pioneering contributions of Solow (1956) and Swan (1956), it has been widely accepted that technological progress is the primary engine of sustained output growth, enabling economies to overcome the limitations of diminishing marginal returns. In this context, AI, as a transformative technological innovation, holds the potential to become a key driver of sustained economic growth, Trammell and Korinek (2023).

Organizations such as the Organisation for Economic Cooperation and Development (OECD) and the European Commission (EC) project that AI could have a profound impact on the economy, potentially driving substantial gains in GDP (Filippucci et al. (2024); Righi et al. (2022)). For instance, Szczepański (2019) estimates that AI could contribute up to 13 trillion USD to the global economy by 2030, positioning it as a key engine of growth, particularly in OECD countries, where advanced technological and digital infrastructures are already in place. In these economies, AI is transforming sectors like marketing and sales, transportation, logistics, and manufacturing, fuelling a digital revolution that is significantly boosting productivity and supporting long-term, sustainable economic growth, OECD (2019). Briggs and Kodnani (2023) estimate that widespread AI adoption could eventually drive a 7% or almost seven trillion USD increase in annual global GDP over a 10-year period.

AI drives economic growth through multiple channels that enhance resource efficiency and stimulate innovation. One key mechanism is its ability to automate routine and time-consuming tasks. This automation frees up human capital for higher value-added activities, thereby improving efficiency and boosting productivity, Agrawal et al. (2019), Brynjolfsson, Li, & Raymond (2025), Bick, Blandin, and Deming (2025). Additionally, AI's powerful capacity to process and analyse vast amounts of data in real time fosters continuous innovation in production methods, leading to the creation of new products and services, Furman & Seamans (2019). Beyond its ability to significantly enhance total factor productivity by enabling more effective use of both human and capital inputs, AI has also the ability to enhance the competitiveness of firms. It empowers businesses to innovate continuously and respond to market shifts with greater agility and precision. Brynjolfsson and McAfee (2014) emphasize that AI encourages firms to embrace knowledge development and constant innovation, essential traits for staying adaptive in an increasingly competitive global market. Moreover, technological change driven by AI tends to be skill-biased; however, the extent to which different skills benefit from AI advancements depends on whether AI acts as a substitute or a complement. Empirical studies using microdata have yielded mixed and sometimes contradictory findings on this relationship. For instance, Bughin (2025) based on data from a global survey across 14 industries and 10 countries finds that while AI is skill-biased in favour of more advanced skills, the effect of AI on skill demand is usually positive for most skills. Brynjolfsson, Li, & Raymond (2025) study the effect of generative AI on productivity and worker experience in the customer-service sector and find that less-skilled workers benefit more.

There may also be different effects of AI on economic growth in the short and long run. In the short run, the impact of AI may be moderated by some transition factors, such as workforce adjustments and the initial costs of technological adoption. Expanding the use of AI requires large investments and at least some skilled labour, as well as a number of changes to production processes. Concerns about a potential surge in technological unemployment due to the unprecedented scale and impact of these innovations could also slow their adoption. These initial costs can cause economic growth to slow down, and thus it may take some time to realise that AI is having an impact on the economy.

Three recent studies examine the impact of AI on economic growth. While Gonzales (2023) and Kalai, Becha, and Helali (2024) do so directly, Parteka and Kordalska (2023) explore it through the lens of labour productivity. Our study builds on this prior research by examining the impact of AI on macroeconomic performance, with a particular focus on OECD countries and the distinction between short- and long-run effects. These three related studies reach different conclusion on the impact of AI on macroeconomic performance, the measure of which differs across studies, as well as the sample of countries analysed, time coverage and estimation procedures applied. Table 1 provides a summary and overview of the former studies.

Table 1. Summary and overview of prior background studies

Reference	Sample	Methods	Dependent variable	Explanatory variables	Main Results
Gonzales (2023)	165 countries 1970-2019 (data at 5-year intervals)	GMM	Growth of real GDP per capita	AI patents per million people. Gross capital formation per capita. Human capita index. Population growth. Government expenditure per capita. Trade openness. Inflation.	AI has a positive effect on growth , stronger in advanced economies. The effect is weaker or non-significant in developing countries.
Kalai, Becha, & Helali (2024)	30 European countries 2000-2021	PMG-ARDL PMG-NARDL	Growth of real GDP	Patents for technologies related to artificial intelligence. Labour force participation rate. Gross fixed capital formation (% of GDP). Foreign direct investment (% of GDP). R&D expenses (% of GDP). Inflation (% of consumer price index)..	AI has a positive long-run impact on output and growth. Evidence of asymmetric effects: negative shocks to AI have a stronger detrimental impact than the positive effect of AI increases.
Parteka & Kordalska (2023)	35 OECD plus 28 non-OECD countries 1985-2017 (5-period moving average)	OLS with fixed effects. IV estimation.	Labour productivity (output per hour worked/ per person employed) growth	AI patents identified by the applicant's country of residence per millions of persons employed. AI patents identified by the inventor's country of residence per millions of persons employed. Number of peer-reviewed AI scientific publications recorded in the Elsevier/Scopus database. General innovation. Human capital index. Trade openness. Regulatory quality index.	Limited evidence that AI patent stocks significantly drive productivity growth at aggregate level.

AI has been shown to positively influence economic growth by Gonzales (2023) that conducted a panel data study analysing the impact of AI on economic growth in both advanced and developing economies over the period from 1970 to 2019, with data taken at five-year intervals, covering a total of 165 countries. The study measured AI-driven technological adoption through the number of AI-related patents and included this proxy as the explanatory variable of interest in an ad hoc growth regression based on an aggregate Cobb-Douglas production function with physical and human capital. The level of technology is assumed to be endogenous, a la Romer (1990), and determined by AI related innovation. To address issues of endogeneity and reverse causality the growth regression was estimated using the Generalized Method of Moments (GMM). The findings indicate that AI has a positive effect on economic growth, measured as the growth rate of real GDP per capita, particularly in advanced economies that possess the capacity to implement and leverage these technologies effectively. In developing countries, the link between AI and economic growth tends to be weaker or non-existent. For a smaller and more homogenous group of countries composed of 30 European countries and distinguishing between medium- and long-term effects for a shorter overall period, 2000-2021, Kalai, Becha, and Helali (2024) also conclude, using symmetric (PMG-ARDL) and asymmetric (PMG-NARDL) models derived from an endogenous growth model as in Gonzales (2023), that there is positive impact of AI on growth to which accrues a positive long-run impact on the level of output, identifying also an asymmetric effect corresponding to a slightly more intense detrimental growth impact from a negative shock to AI. The dependent variable is the growth rate of total real GDP and the explanatory variable of interest the number of AI patents, considered alongside other determinants of growth identified by previous literature.

Parteka and Kordalska (2023) explore the relationship between AI and aggregate labour productivity using data on AI-related patents and scientific publications across 35 OECD and 28 non-OECD countries from 1985 to 2017. Despite the evident increase in AI knowledge production, as reflected in the growth of patent and publication activity, the authors found limited evidence that accumulated AI patent stocks significantly contribute to productivity growth, both in OECD countries and in the broader sample. They suggest that other dynamics may be at play at the micro and sectoral levels, where the adoption of digital technologies could lead to productivity gains at the firm level, without necessarily translating into growth at the aggregate level. Furthermore, the study highlights that group preconditions, such as investment in human capital and supportive innovation policies, play a crucial role in shaping AI's economic impact.

In summary, the role of technological progress as a primary determinant of modern economic growth and long-term improvements in living standards is undeniable. However, its effects are frequently realized with a time lag. This delay can be attributed to adjustment costs, including the requirement for supporting investments and workforce reskilling, as well as the time needed for consequent sectoral transformations to fully manifest. This research examines these dynamics in relation to AI, a rapidly advancing technology whose increasing prevalence has fostered substantial expectations for its potential to enhance macroeconomic outcomes and societal well-being. We also examine whether the growth effects of AI vary across countries with different skill endowments, providing insight into whether AI complements or substitutes human capabilities at the aggregate level. To investigate the impact of AI adoption on economic growth and standards of living and the role of human capital we consider a sample of 35 OECD countries observed annually over the period 1995-2017 and estimate a panel autoregressive distributed lag (ARDL) model, assessing the existence of long-run relationships and identifying short-run impacts.

The contribution of this study is twofold. First, it adds to the discussion on the economic effects of AI adoption and what types of labour benefit more from AI advancements by taking stock of the evidence at the macroeconomic level. At the microeconomic level previous studies have identified productivity gains from AI adoption within firms, e.g. Damioli, Van Roy, and Vertesy (2021) using a worldwide sample of 5257 companies, and Zhai and Liu (2023) using a sample of Chinese-listed companies, but less is known about its effects for the aggregate economy. Micro-level evidence on the role of human capital remains mixed. Bughin (2025) finds that although AI is biased toward higher skills, it generally boosts demand across most skill levels. Brynjolfsson, Li, & Raymond (2025) show that generative AI can particularly benefit lower-skilled workers, enhancing their productivity. Second, we extend the limited set of papers examining the macroeconomic outcomes of AI adoption by disentangling the respective short and long-run effects. As Hornstein (2024) emphasizes, despite AI's considerable potential, there is still uncertainty regarding the extent to which it will be realised and the pace at which it will develop.

This study is organised in four sections. Section 1 contains the introduction including a literature overview of the relationship between AI and economic growth. Section 2 describes the main variables and defines the empirical model. Based on those foundations, Section 3 contains the findings and discusses the short- and long-run effects of AI adoption, as well as the possible role of human capital; while section 4 concludes.

2. Data and Methods

Our analysis draws on a panel dataset of annual observations from 1995 to 2017 covering 35 of the current 38 OECD member countries as this group of countries is better positioned to make AI a key engine of growth with advanced technological and digital infrastructures already in place. The OECD member countries not included are Colombia, Costa Rica and Lithuania. The selection of countries and time period was guided by the availability of data for AI adoption, as well as by the goal of including a broad range of countries.

2.1. Main variables

Economic growth is measured as the first difference of the log of real GDP per capita (y) from the PWT v.10.01, Feenstra, Inklaar, & Timmer (2015). Real GDP per capita is calculated as the ratio between GDP at constant 2017 USD and population, a standard measure of standards of living.

AI-related innovation and general innovation are measured at the country level using data from Parteka and Kordalska (2023) that compute three different proxies for AI adoption: (i) the number of patents by applicants, identified in this study as ai^{APP}; (ii) the number of patents by inventors (ai^{INV}), and (iii) the number of scientific publications (ai^{PUB}), all per million people employed. The same rationale applies to the proxy for general innovation measured by the overall number of patents by applicants (inn^{APP}) or by inventors (inn^{INV}) and by the overall number of publications (inn^{PUB}), all per million people employed.

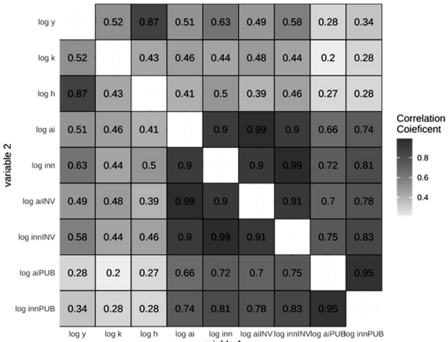
Besides innovation/productivity, the contribution of the remaining immediate sources of growth corresponding to physical and human capital is measured, respectively, using the capital stock at constant 2017 USD per capita (k) and a human capital index (h) that combines average years of education and returns to education, both from the PWT 10.01.

Table 2 contains summary statistics for the variables included in our baseline model, described in detail in the next section, and Figure 1 presents the correlation matrix. A positive simple correlation between AI and the log of real GDP per capita is found for our sample as reported in Figure 1. Notice also that the correlation is higher for the overall innovation measure confirming the idea that for the OECD countries in our sample, composed mostly of advanced knowledge-based economies, technological progress is a key driver of growth and rising living standards.

Table 2. Summary statistics

Variables	N	mean	st.dev.	min	max	median	skewness	kurtosis
log y	805	10.40	0.438	9.170	11.46	0.192	-0.480	3.030
log h	805	1.149	0.131	0.617	1.337	0.0172	-1.300	4.867
log k	805	11.80	0.551	10.05	12.88	0.303	0.303	-0.913
log ai^{APP}	805	1.805	1.862	0	7.225	3.467	0.941	3.120
log ai^{INV}	805	1.882	1.833	0	7.182	3.361	0.905	3.067
log ai^{PUB}	805	5.092	1.580	0	9.229	2.497	-0.546	3.603
log inn^{APP}	805	6.254	2.371	0.295	11.12	5.621	0.0226	2.260
log inn^{INV}	805	6.324	2.306	1.065	11.11	5.317	0.0577	2.236
log inn^{PUB}	805	9.749	1.556	4.796	13.46	2.420	-0.418	3.327

Figure 1. Correlation matrix



2.2. The baseline model

To estimate the effects of AI on economic growth and standards of living, we consider an expanded neoclassical growth model (see e.g. Gonzales (2023) and Kalai, Becha, and Helali (2024)) with a standard aggregate production function given by Y = AF(K,H,L), where Y is output, A is total factor productivity, K is the physical capital stock, H is the human capital stock and L is the labour force.[1] Writing the production function in intensive form, i.e. dividing both sides by L, log-linearising it, and considering that productivity depends on technology, namely AI, we start by assuming that there is a long-run relationship between per capita output and its determinants as expressed in equation (1):

$$\mathrm{logy}_{i,t} = \alpha_{0,i} + \alpha_1 \mathrm{logk}_{i,t} + \alpha_2 \mathrm{logh}_{i,t} + \alpha_3 \mathrm{logai}_{i,t} + \alpha_4 \mathrm{loginn}_{i,t} + \varepsilon_{i,t} \tag{1}$$

where i = 1,2,…,N denotes the country and t = 1,2,…,T the years, y is output per capita, k is physical capital per capita, h is human capital per capita, AI adoption is denoted by ai, inn is a measure for general or overall innovation to control for the additional effort towards AI for a given technological level, $\alpha_{0,i}$ is a country-specific component and $\varepsilon_{i,t}$ stands for the error term.

Assuming the existence of a stable long-run relationship between the former variables, that we examine further along this section using panel cointegration tests, we next define a panel Autoregressive Distributed Lag (ARDL) model given by equation (2):

$$\Delta logy_{it} = \mu_i + \beta_1 \Delta logk_{i,t} + \beta_2 \Delta logh_{i,t} + \beta_3 \Delta logai_{i,t} + \beta_4 \Delta loginn_{i,t} + \gamma logy_{i,t-1} + \alpha_1 logk_{i,t-1} + \alpha_2 logh_{i,t-1} + \alpha_3 logai_{i,t-1} + \alpha_4 loginn_{i,t-1} + \epsilon_{it} \tag{2}$$

where Δ is the first difference operator, μ_i denotes the country fixed effects, the β coefficients can be interpreted as short-run effects, the α coefficients as the long-run effects, and γ is the coefficient associated with the error correction term that measures the speed of adjustment to the long-run equilibrium given by equation (1). The error correction term in this context can also be interpreted as a test of the existence of convergence among the countries in the sample in which case we expect it to display a statistically significant negative coefficient.

An advantage of this specification is that the dependent variable is the rate of economic growth, which allows us to observe both the short-run effects of the former variables on economic growth but also how they impact the level of per capita income in the long-run. The adoption of AI is expected to positively impact economic growth in both the short- and long- term, resulting in positive coefficients for these effects. Similarly, the literature suggests

[1] As mentioned by an anonymous referee we treat AI adoption as an increase in the total factor productivity (TFP) index *A* and thus implicitly assume Hicks-neutral technological progress. In practice, however, AI does not enhance the productivity of capital and labour uniformly. As highlighted in modern task-based models, AI and automation technologies alter the allocation of tasks between capital and labour, simultaneously replacing workers with machines in certain functions while complementing human labour in others, see e.g. Acemoglu and Restrepo (2019), Autor (2015). These heterogeneous and factor-biased effects are effectively averaged out in our empirical specification, which is not problematic given that our objective is not to identify the direction or bias of technical change. We thank the anonymous referee for suggesting that we include this clarification.

that physical capital, human capital, and general innovation also contribute positively to economic growth. Therefore, we anticipate positive coefficients for these variables in both the short- and the long-run. In the presence of cointegration, this type of panel ARDL models have been introduced by Pesaran and Smith (1995) and Pesaran, Yongcheol, and and Smith (1999) to disentangle the short- from the long-run effects between the regressors and the dependent variable. As our panel model is dynamic in nature, we make use of the estimation techniques proposed in Arellano and Bond (1991), the difference-GMM (diff-GMM), and in Arellano and Bover (1995) and Blundell and Bond (1998), the system GMM (sys-GMM). These techniques allow us not only to deal with the dynamic panel specification but also with the endogeneity issues that may arise from the potential feedback effect between per capita income and innovation, both the overall level and the AI-directed one, as countries with higher income levels are likelier to allocate resources to innovation activities.

A pre-requisite for the estimation of a panel ARDL model is that the order of integration of the variables included are a mix of I(0) and I(1) or a combination of both, and none should be integrated of order 2, I(2). To ensure that this is the case we test for the presence of unit roots in our panel data series using the Pesaran (2007) cross-sectionally augmented IPS (CIPS) panel unit root test for which the null hypothesis is that of the existence of a unit root in the series. From the results presented in Table 3 we can see that, aside from the human capital variable, we have a combination of I(0) and I(1) variables in our model. As for human capital, we test its second difference for the existence of a unit root and obtain evidence that it is stationary.

Table 3. Results of the CIPS panel unit root tests

	No trend				**With Trend**			
Variables	**0 lags**	**1 lag**	**2 lags**	**3 lags**	**0 lags**	**1 lag**	**2 lags**	**3 lags**
$log\ y$	0.170	0.000	0.002	0.019	0.851	0.001	0.341	0.808
$log\ h$	1.000	0.989	0.990	0.965	1.000	1.000	1.000	1.000
$log\ k$	0.020	0.000	0.001	0.000	0.038	0.000	0.001	0.004
$log\ ai^{APP}$	0.000	0.000	0.102	0.161	0.000	0.001	0.796	0.957
$log\ inn^{APP}$	0.000	0.000	0.000	0.062	0.002	0.033	0.028	0.351
$log\ ai^{INV}$	0.000	0.000	0.147	0.383	0.000	0.000	0.844	0.877
$log\ inn^{INV}$	0.000	0.000	0.000	0.041	0.000	0.002	0.001	0.187
$log\ ai^{PUB}$	0.000	0.008	0.000	0.000	0.000	0.130	0.000	0.026
$log\ inn^{PUB}$	0.000	0.000	0.000	0.286	0.000	0.487	0.000	0.139
$\Delta log\ y$	0.000	0.000	0.000	0.129	0.000	0.000	0.582	0.999
$\Delta log\ h$	1.000	1.000	1.000	1.000	0.984	0.998	0.999	0.995
$\Delta log\ k$	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.080
$\Delta log\ ai^{APP}$	0.000	0.000	0.213	0.498	0.000	0.020	0.973	0.999
$\Delta log\ inn^{APP}$	0.000	0.000	0.038	0.013	0.002	0.003	0.091	0.023

$\Delta log\ ai^{INV}$	0.000	0.000	0.032	0.330	0.000	0.000	0.411	0.992
$\Delta log\ inn^{INV}$	0.000	0.000	0.000	0.000	0.001	0.198	0.429	0.198
$\Delta log\ ai^{PUB}$	0.000	0.176	0.100	0.517	0.000	0.473	0.000	0.018
$\Delta log\ inn^{PUB}$	0.142	0.836	0.025	0.579	0.235	0.965	0.001	0.971

Notes: The table contains the p-values for the CIPS panel unit root test (Pesaran, 2007). The null of the test is the existence of a unit root in the series.

Based on the above described results, we modify our long-run model, which now considers Δh instead of h, given by equation (3):

$$logy_{it} = \alpha_{0,i} + \alpha_1 logk_{i,t} + \alpha_2 \Delta logh_{i,t} + \alpha_3 logai_{i,t} + \alpha_4 loginn_{i,t} + \varepsilon_{it} \tag{3}$$

and the corresponding panel ARDL model is given by equation (4):

$$\Delta logy_{it} = \mu_i + \beta_1 \Delta logk_{i,t} + \beta_2 \Delta^2 logh_{i,t} + \beta_3 \Delta logai_{i,t} + \beta_4 \Delta loginn_{i,t} + \gamma logy_{i,t-1} + \alpha_1 logk_{i,t-1} + \alpha_2 \Delta logh_{i,t-1} + \alpha_3 logai_{i,t-1} + \alpha_4 loginn_{i,t-1} + \epsilon_{it} \tag{4}$$

To further validate the models given by equations (3) and (4) we perform panel cointegration tests (see Table 4) using the procedure proposed by Westerlund (2005). The null hypothesis of this test is the absence of cointegration, and we consider two versions of the test. The first, defines as the alternative hypothesis that only some of the cross-sectional units display cointegration while the second version takes as the alternative hypothesis the possibility that all the panel units display cointegration. In both cases, we perform the test with and without a trend in the model. The results provide evidence in favour of the existence of cointegration among the variables we consider in the long-run regression given by equation (3).

Table 4. Results of the Westerlund (2005) panel cointegration tests

		No Trend	**With Trend**
APP	All Panels	0.0773	0.3935
	Some Panels	0.0453	0.0379
INV	All Panels	0.1157	0.1644
	Some Panels	0.0686	0.0060
PUB	All Panels	0.1631	0.0306
	Some Panels	0.1326	0.0008

Notes: the table contains the p-values for the Westerlund panel cointegration test Westerlund (2005). The null of the test is the absence of cointegration among the series.

3. Findings

We start by presenting the results of the estimation of the baseline panel ARDL model. We next present the outcomes of several robustness checks. Finally, we analyse nonlinear growth effects of AI through human capital.

3.1. Baseline results

The estimation results of our baseline model with diff-GMM and sys-GMM are reported in Table 5. Besides addressing omitted variable bias due to unmeasured differences between countries, these methodologies account for the possibility of endogeneity resulting from the consideration of the lagged dependent variable in dynamic panel models by using GMM-style internal instruments. In addition to this, where we treat $logy_{i,t-1}$ as predetermined, we also consider the variables related to AI and innovation to be endogenous – and similarly to lagged income we also use GMM-style internal instruments – as it is likely to exist a feedback effect between these and economic growth which can generate a simultaneity issue in the model. More advanced economies will have an incentive to adopt AI faster since they already possess related know-how, e.g. because automation is already well-established, and the necessary infrastructure is already in place, or because they have higher wages as total factor productivity is higher and higher wages induce firms in advanced economies to use labour-replacing AI more intensively, Alonso, Kothari, & Rehman (2020). To keep the number of moment conditions in the models tractable we use the Roodman (2009) collapse procedure and selected the number of instruments (lagged values) immediately below the number of countries or cross-section units as recommended in the literature. We also estimated equation (4) accounting only for omitted variable bias through the fixed effects estimator (results available from the authors).

The results using the first differenced GMM estimator (Diff-GMM) presented in Table 5 point to positive and statistically significant short- and long-run estimated coefficients for the AI measures using data on patents, both patents by applicants and patents by inventors. For AI measures based on scientific publications, however, none of the estimated coefficients are statistically significant. The latter also applies to the results for all AI measures using the Sys-GMM estimator. However, while model adequacy tests regarding instrument validity and model specification present no problems for Diff-GMM, the same does not apply when using Sys-GMM. Indeed, the second order autocorrelation (AR2) tests do not detect problems for Diff-GMM as the null hypothesis is never rejected at conventional significance levels, but with Sys-GMM AR2 still applies. The Hansen tests also never reject the null hypothesis that the instruments are valid with Diff-GMM, but with Sys-GMM the null is either rejected or the p-value is borderline (very close to 10%). These diagnostic tests for Sys-GMM advise caution regarding the reliability our results applying the Sys-GMM methodology. This is reinforced by the fact that lagged income presents a negative and statistically significant coefficient, which is in line with the results from the cointegration tests, indicating that a lower starting point for per capita income is associated with higher economic growth rates, but the estimated coefficient is only statistically significant when using Diff-GMM and patents-based AI data. Given the specification we adopted for our model, the negative sign for the estimated coefficient of lagged income can also be interpreted as an error correction term for disequilibria relative to the long-run relationship. The estimated coefficients for physical and human capital, when statistically significant, in both the short- and the long-run display the expected signs, positive.

Table 5. Results for the baseline model

	Diff-GMM			Sys-GMM		
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation/AI	*APP*	*INV*	*PUB*	*APP*	*INV*	*PUB*
$\Delta^2 logh_{i,t}$	2.357	2.890*	0.371	0.259	0.168	0.158
	(1.998)	(1.511)	(1.941)	(1.057)	(1.307)	(1.172)
$\Delta logk_{i,t}$	0.173**	0.151*	0.0621	0.123	0.132	0.124*
	(0.0776)	(0.0775)	(0.0668)	(0.0782)	(0.0925)	(0.0659)
$\Delta logai^{APP}_{i,t}$	0.0639***			-0.00692		
	(0.0231)			(0.0103)		
$\Delta loginn^{APP}_{i,t}$	0.132			0.00885		
	(0.0937)			(0.0307)		
$logy_{i,t-1}$	-0.663***	-0.592***	0.0908	-0.0360	-0.0721	-0.0208
	(0.203)	(0.202)	(0.0726)	(0.0489)	(0.0490)	(0.0415)
$\Delta logh_{i,t-1}$	2.425	0.814	-0.180	0.0225	-0.0672	-0.642
	(2.248)	(1.765)	(1.556)	(0.871)	(0.857)	(1.092)
$logk_{i,t-1}$	0.127*	0.111*	-0.104**	0.00518	0.0314	0.00158
	(0.0710)	(0.0637)	(0.0525)	(0.0266)	(0.0284)	(0.0244)
$logai^{APP}_{i,t-1}$	0.0724***			-0.00504		
	(0.0196)			(0.00896)		
$loginn^{APP}_{i,t-1}$	0.141***			0.00722		
	(0.0542)			(0.00838)		
$\Delta logai^{INV}_{i,t}$		0.0547**			0.00363	
		(0.0259)			(0.0157)	
$logai^{INV}_{i,t-1}$		0.0584***			-0.00164	
		(0.0193)			(0.0110)	
$\Delta loginn^{INV}_{i,t}$		0.109			-0.0130	
		(0.0718)			(0.0328)	
$loginn^{INV}_{i,t-1}$		0.117*			0.00385	
		(0.0693)			(0.00730)	
$\Delta logai^{PUB}_{i,t}$			0.0188			0.0215
			(0.0275)			(0.0136)
$logai^{PUB}_{i,t-1}$			-0.00887			0.00886
			(0.0214)			(0.0118)
$\Delta loginn^{PUB}_{i,t}$			0.00295			-0.0120
			(0.0426)			(0.0219)
$loginn^{PUB}_{i,t-1}$			0.0208			-0.0108
			(0.0311)			(0.0151)

	Diff-GMM			Sys-GMM		
	(1)	(2)	(3)	(4)	(5)	(6)
Observations	680	680	680	714	714	714
No. of Countries	34	34	34	34	34	34
No. of instruments	24	24	24	30	30	30
AR1 (p-value)	0.151	0.0730	0.000712	0.000349	0.000620	0.000439
AR2 (p-value)	0.153	0.238	0.216	0.0909	0.0726	0.161
Hansen-J	17.67	19.28	20.27	27.92	30.19	26.98
Hansen-J (p-value)	0.280	0.201	0.162	0.111	0.0668	0.136

Notes: robust standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.010$.

3.2. Robustness analysis

In this subsection section we present the outcomes of several robustness checks: (i) the consideration of different lag orders in the ARDL model; (ii) including other growth determinants in the set of control variables; (iii) measuring AI adoption as a stock variable; and (iv) testing for the stability of the estimated coefficients. We conducted this analysis using models that included each of the three proxies for AI and overall innovation variables, as in the previous section.

3.2.1. *Different lag orders*

As the results may be sensitive to the number of lags included in the short-run dynamics of the ARDL model, our first robustness check re-estimates each of the three model specifications using alternative lag lengths for the short-run terms. Due to data restrictions and given that we are using annual data we only experiment with up to two lags. Across the various alternative specifications we test, see Tables 6-8, the core results remain largely consistent although introducing additional lags leads to a loss of statistical significance also for Diff-GMM results. However, the BIC criterion favours models without additional lags in the short-run terms, corresponding to the baseline models from the previous section and replicated in columns (1) and (4) of Tables 6 to 8.

Table 6. Results using different lag orders – ai^{APP}

	Diff-GMM			Sys-GMM		
	No lags	1 lag	2 lags	No lags	1 lag	2 lags
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta^2 logh_{i,t}$	2.357	1.928	2.285	0.259	-2.849	11.24
	(1.998)	(1.742)	(2.792)	(1.057)	(4.423)	(8.528)
$\Delta logk_{i,t}$	0.173**	0.0999	0.0671	0.123	0.171**	0.0348
	(0.0776)	(0.138)	(0.306)	(0.0782)	(0.0829)	(0.127)
$\Delta logai^{APP}_{i,t}$	0.0639***	0.0443	0.0286	-0.00692	0.0239	0.0519
	(0.0231)	(0.0460)	(0.0690)	(0.0103)	(0.0257)	(0.0404)
$\Delta loginn^{APP}_{i,t}$	0.132	0.0753	0.0534	0.00885	0.161**	-0.201*
	(0.0937)	(0.0467)	(0.590)	(0.0307)	(0.0751)	(0.120)
$logy_{i,t-1}$	-0.663***	-0.973*	-0.830	-0.0360	-0.0719	-0.116
	(0.203)	(0.558)	(1.154)	(0.0489)	(0.0773)	(0.104)
$\Delta logh_{i,t-1}$	2.425	-37.98*	-66.62	0.0225	2.618	-2.440
	(2.248)	(22.86)	(62.81)	(0.871)	(3.207)	(8.394)
$\Delta^2 logh_{i,t-1}$		40.60*	70.38		-14.66	39.74
		(21.90)	(61.81)		(16.89)	(37.85)
$\Delta^2 logh_{i,t-2}$			3.988			-43.28*
			(64.36)			(22.91)
$logk_{i,t-1}$	0.127*	0.165	0.0331	0.00518	0.0313	0.0454
	(0.0710)	(0.173)	(0.241)	(0.0266)	(0.0478)	(0.0565)
$\Delta logk_{i,t-1}$		-0.0870	-0.0429		0.368	-0.152
		(0.117)	(0.351)		(0.262)	(0.294)
$\Delta logk_{i,t-2}$			0.450			0.1000
			(0.656)			(0.389)
$logai^{APP}_{i,t-1}$	0.0724***	0.0994*	0.0872	-0.00504	0.0109	-0.00178
	(0.0196)	(0.0583)	(0.0997)	(0.00896)	(0.0113)	(0.0120)
$\Delta logai^{APP}_{i,t-1}$		-0.0195	-0.00991		0.00400	0.0374
		(0.0120)	(0.0469)		(0.00922)	(0.0240)
$\Delta logai^{APP}_{i,t-2}$			0.00658			0.0251
			(0.0352)			(0.0221)
$loginn^{APP}_{i,t-1}$	0.141***	0.172*	0.169	0.00722	0.00734	-0.00129
	(0.0542)	(0.104)	(0.256)	(0.00838)	(0.0111)	(0.0167)
$\Delta loginn^{APP}_{i,t-1}$		0.000233	0.0452		0.0525**	0.0265
		(0.0296)	(0.135)		(0.0213)	(0.0433)
$\Delta loginn^{APP}_{i,t-2}$			0.0218			-0.0481
			(0.0995)			(0.0351)
Observations	680	646	612	714	680	646
No. of Countries	34	34	34	34	34	34
No. of instruments	24	22	20	30	28	26
AR1 (p-value)	0.151	0.841	0.993	0.000	0.006	0.034
AR2 (p-value)	0.153	0.639	0.717	0.091	0.252	0.843
Hansen-J	17.671	5.544	1.438	27.923	20.102	8.940
Hansen-J (p-value)	0.280	0.785	0.697	0.111	0.127	0.347
BIC	2039.347	2574.424	2485.685	-4373.548	-3624.726	-2760.609

Notes: robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Table 7. Results using different lag orders – ai^{INV}

	Diff-GMM			Sys-GMM		
	No lags	1 lag	2 lags	No lags	1 lag	2 lags
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta^2 logh_{i,t}$	2.890*	2.741	2.206	0.168	6.176	13.86*
	(1.511)	(2.046)	(3.290)	(1.307)	(5.552)	(7.710)
$\Delta logk_{i,t}$	0.151*	0.101	0.0143	0.132	0.0755	0.0480
	(0.0775)	(0.159)	(0.644)	(0.0925)	(0.116)	(0.172)
$\Delta logai^{INV}_{i,t}$	0.0547**	0.0369	-0.0204	0.00363	-0.00963	-0.00363
	(0.0259)	(0.0333)	(0.129)	(0.0157)	(0.0343)	(0.108)
$\Delta loginn^{INV}_{i,t}$	0.109	0.160	0.293	-0.0130	0.0834	-0.0337
	(0.0718)	(0.127)	(0.217)	(0.0328)	(0.0615)	(0.135)
$logy_{i,t-1}$	-0.592***	-0.564	-0.546	-0.0721	-0.0375	-0.00960
	(0.202)	(0.495)	(1.098)	(0.0490)	(0.0708)	(0.163)
$\Delta logh_{i,t-1}$	0.814	-32.51	-68.62	-0.0672	-6.033	-14.70*
	(1.765)	(32.60)	(55.04)	(0.857)	(7.484)	(8.817)
$\Delta^2 logh_{i,t-1}$		33.68	69.22		24.74	64.94*
		(33.02)	(54.13)		(30.12)	(34.44)
$\Delta^2 logh_{i,t-2}$			13.16			-15.19
			(124.8)			(35.40)
$logk_{i,t-1}$	0.111*	0.0824	0.0154	0.0314	0.0134	-0.0159
	(0.0637)	(0.0830)	(0.208)	(0.0284)	(0.0355)	(0.0772)
$\Delta logk_{i,t-1}$		-0.00680	-0.0445		0.0762	-0.141
		(0.136)	(0.319)		(0.286)	(0.927)
$\Delta logk_{i,t-2}$			0.289			0.0392
			(0.545)			(0.339)
$logai^{INV}_{i,t-1}$	0.0584***	0.0528	0.0137	-0.00164	-0.00845	-0.0192
	(0.0193)	(0.0388)	(0.126)	(0.0110)	(0.0165)	(0.0385)
$\Delta logai^{INV}_{i,t-1}$		-0.000696	0.00301		0.00940	0.0304
		(0.0120)	(0.0557)		(0.00859)	(0.0314)
$\Delta logai^{INV}_{i,t-2}$			-0.00544			0.0116
			(0.0632)			(0.0293)
$loginn^{INV}_{i,t-1}$	0.117*	0.0928	0.158	0.00385	0.00306	0.00322
	(0.0693)	(0.127)	(0.259)	(0.00730)	(0.00982)	(0.0202)
$\Delta loginn^{INV}_{i,t-1}$		0.0286	0.0892		0.0553	0.0577
		(0.0486)	(0.230)		(0.0375)	(0.0628)
$\Delta loginn^{INV}_{i,t-2}$			0.0454			0.00635
			(0.0488)			(0.0597)
Observations	680	646	612	714	680	646
No. of Countries	34	34	34	34	34	34
No. of instruments	24	22	20	30	28	26
AR1 (p-value)	0.073	0.517	0.991	0.001	0.035	0.285
AR2 (p-value)	0.238	0.517	0.891	0.073	0.272	0.334
Hansen-J	19.279	12.808	1.786	30.189	21.918	11.236
Hansen-J (p-value)	0.201	0.171	0.618	0.067	0.080	0.189
BIC	1919.975	1951.134	1968.215	-4332.376	-3710.615	-2639.977

Notes: robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Table 8. Results using different lag orders – ai^{PUB}

	Diff-GMM			Sys-GMM		
	No lags	1 lag	2 lags	No lags	1 lag	2 lags
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta^2 logh_{i,t}$	0.371	3.337**	2.649	0.158	1.827	-1.519
	(1.941)	(1.441)	(2.481)	(1.172)	(1.395)	(3.459)
$\Delta logk_{i,t}$	0.0621	0.0169	0.247	0.124*	0.0967*	0.167
	(0.0668)	(0.0954)	(0.187)	(0.0659)	(0.0496)	(0.164)
$\Delta logai^{PUB}_{i,t}$	0.0188	-0.113	0.0542	0.0215	0.00194	0.0420
	(0.0275)	(0.0730)	(0.162)	(0.0136)	(0.0252)	(0.123)
$\Delta loginn^{PUB}_{i,t}$	0.00295	0.152	0.326	-0.0120	0.0380	0.212
	(0.0426)	(0.226)	(0.472)	(0.0219)	(0.0449)	(0.377)
$logy_{i,t-1}$	0.0908	0.348	-0.111	-0.0208	0.0655	-0.146
	(0.0726)	(0.613)	(0.820)	(0.0415)	(0.0613)	(0.306)
$\Delta logh_{i,t-1}$	-0.180	-18.69	45.90	-0.642	0.999	-5.519
	(1.556)	(28.95)	(39.44)	(1.092)	(1.705)	(12.70)
$\Delta^2 logh_{i,t-1}$		20.65	-44.14		0.625	1.558
		(28.83)	(39.44)		(4.925)	(18.37)
$\Delta^2 logh_{i,t-2}$			8.490			26.98
			(44.82)			(54.56)
$logk_{i,t-1}$	-0.104**	-0.130	0.213	0.00158	-0.0553	0.0743
	(0.0525)	(0.0994)	(0.271)	(0.0244)	(0.0425)	(0.195)
$\Delta logk_{i,t-1}$		-0.213	-0.564		-0.274**	-0.325
		(0.345)	(0.395)		(0.118)	(0.571)
$\Delta logk_{i,t-2}$			0.769*			0.514
			(0.462)			(0.320)
$logai^{PUB}_{i,t-1}$	-0.00887	-0.114	0.120	0.00886	0.0235**	0.0135
	(0.0214)	(0.107)	(0.200)	(0.0118)	(0.0111)	(0.0376)
$\Delta logai^{PUB}_{i,t-1}$		-0.00724	-0.0283		-0.00776	-0.00143
		(0.0123)	(0.0443)		(0.00927)	(0.0373)
$\Delta logai^{PUB}_{i,t-2}$			-0.0304*			-0.0141
			(0.0167)			(0.0155)
$loginn^{PUB}_{i,t-1}$	0.0208	0.116	-0.205	-0.0108	-0.0226*	-0.0184
	(0.0311)	(0.153)	(0.268)	(0.0151)	(0.0135)	(0.0337)
$\Delta loginn^{PUB}_{i,t-1}$		0.0188	0.0571		0.0167	0.0130
		(0.0238)	(0.0449)		(0.0148)	(0.0409)
$\Delta loginn^{PUB}_{i,t-2}$			0.0422*			0.0171
			(0.0225)			(0.0167)
Observations	680	646	612	714	680	646
No. of Countries	34	34	34	34	34	34
No. of instruments	24	22	20	30	28	26
AR1 (p-value)	0.001	0.043	0.504	0.000	0.003	0.387
AR2 (p-value)	0.216	0.462	0.704	0.161	0.308	0.536
Hansen-J	20.269	5.776	1.498	26.978	16.760	14.951
Hansen-J (p-value)	0.162	0.762	0.683	0.136	0.269	0.060
BIC	-2519.428	1224.373	-1215.983	-4378.942	-3993.296	-3247.209

Notes: robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010

3.2.2. *Additional controls*

Since we use a standard growth regression framework, we introduce additional control variables to both allow for potential model extensions given the 'open-endedness' of growth theory and to mitigate the risk of omitted variable bias, see e.g. Brock and Durlauf (2001), D'Andrea (2022), Chen and Yu (2024). As a robustness check, we add these extra controls, all previously suggested in the literature, one at a time, to evaluate the extent to which they affect the results for our baseline model. The additional control variables are *trade*, the degree of openness of an economy measured as the ratio between the sum of export and imports and GDP, *rqe*, a measure of regulatory quality retrieved from Parteka and Kordalska (2023), *inds*, the value added by the manufacturing sector as a percentage of GDP, *g*, public consumption as a percentage of GDP, *inf*, the inflation rate measured as the growth rate of the consumer price index, *fdi*, net inflows of foreign direct investment as a percentage of GDP, and *urban*, the urban population as a percentage of total population. Data for these control variables were retrieved from the World Bank online Databank, except for *rqe*. The inclusion of these additional variables does not significantly alter our findings regarding the relationship between AI, overall innovation, and economic growth across any of the previously estimated model variants, see Tables 9-14. As for the control variables, the most consistent result across the estimated specifications is the negative and statistically significant coefficient for public consumption as a percentage of GDP.

Table 9. Results with Diff-GMM and additional control variables – ai^{APP}

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta^2 logh_{i,t}$	2.357	1.481	2.545	2.188	1.421	4.015*	1.581	2.304
	(1.998)	(2.571)	(2.443)	(1.709)	(1.346)	(2.314)	(2.323)	(1.947)
$\Delta logk_{i,t}$	0.173**	0.181*	0.168**	0.259**	0.158*	0.213**	0.168*	0.168**
	(0.0776)	(0.104)	(0.0760)	(0.102)	(0.0930)	(0.0896)	(0.0897)	(0.0727)
$\Delta logai^{APP}_{i,t}$	0.0639***	0.0491	0.0757**	0.0592*	0.0449*	0.0609**	0.0681***	0.0623***
	(0.0231)	(0.0344)	(0.0336)	(0.0323)	(0.0250)	(0.0259)	(0.0204)	(0.0229)
$\Delta loginn^{APP}_{i,t}$	0.132	0.0997	0.149*	0.150**	0.138**	0.176**	0.145*	0.129
	(0.0937)	(0.0703)	(0.0842)	(0.0683)	(0.0564)	(0.0686)	(0.0792)	(0.0909)
$logy_{i,t-1}$	-0.663***	-0.493**	-0.637***	-0.646***	-0.523***	-0.709***	-0.698***	-0.636***
	(0.203)	(0.203)	(0.194)	(0.208)	(0.197)	(0.200)	(0.171)	(0.219)
$\Delta logh_{i,t-1}$	2.425	1.423	1.471	1.670	0.355	1.598	3.326	2.360
	(2.248)	(2.323)	(2.230)	(1.972)	(1.603)	(2.182)	(2.304)	(2.340)
$logk_{i,t-1}$	0.127*	0.0954	0.130*	0.158*	0.0962	0.156**	0.159**	0.119
	(0.0710)	(0.0721)	(0.0722)	(0.0828)	(0.0745)	(0.0714)	(0.0665)	(0.0762)
$logai^{APP}_{i,t-1}$	0.0724***	0.0476	0.0799***	0.0546**	0.0467**	0.0615***	0.0739***	0.0712***
	(0.0196)	(0.0292)	(0.0275)	(0.0243)	(0.0214)	(0.0220)	(0.0171)	(0.0203)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$loginn^{APP}_{i,t-1}$	0.141***	0.107**	0.137***	0.137***	0.124***	0.138***	0.151***	0.137**
	(0.0542)	(0.0496)	(0.0485)	(0.0490)	(0.0416)	(0.0463)	(0.0516)	(0.0548)
$\Delta trade_{i,t}$		0.00200						
		(0.00142)						
$\Delta rqe_{i,t}$			-0.0637					
			(0.0553)					
$\Delta inds_{i,t}$				0.0237*				
				(0.0126)				
$\Delta g_{i,t}$					-0.031***			
					(0.0106)			
$\Delta inf_{i,t}$						0.00628*		
						(0.00376)		
$\Delta fdi_{i,t}$							0.00190	
							(0.00165)	
$\Delta urban_{i,t}$								-0.0275
								(0.147)
Observations	680	680	680	680	680	680	680	680
No. of Countries	34	34	34	34	34	34	34	34
No. of instruments	24	24	24	24	24	24	24	24
AR1 (p-value)	0.151	0.066	0.070	0.067	0.027	0.066	0.137	0.137
AR2 (p-value)	0.153	0.617	0.372	0.431	0.685	0.807	0.862	0.145
Hansen-J	17.671	20.846	13.562	16.001	15.553	15.328	14.657	17.501
Hansen-J (p-value)	0.280	0.106	0.483	0.313	0.341	0.356	0.402	0.230
BIC	2039.347	1636.655	1952.223	1885.498	1718.234	2096.858	2018.807	1993.661

Notes: robust standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.010$.

Table 10. Results with Sys-GMM and additional control variables – ai^{APP}

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta^2 logh_{i,t}$	0.259	1.180	0.185	0.297	0.112	1.490	0.0193	0.927
	(1.057)	(0.906)	(0.904)	(0.874)	(1.344)	(1.139)	(1.314)	(1.197)
$\Delta logk_{i,t}$	0.123	0.140*	0.139*	0.165**	0.160	0.174**	0.118	0.136**
	(0.0782)	(0.0766)	(0.0811)	(0.0654)	(0.0999)	(0.0771)	(0.0807)	(0.0677)
$\Delta logai^{APP}_{i,t}$	-0.00692	-0.00105	-0.00763	-0.00270	-0.00644	0.00259	-0.00516	-0.00696
	(0.0103)	(0.0121)	(0.0107)	(0.0100)	(0.0119)	(0.0113)	(0.0102)	(0.00614)
$\Delta loginn^{APP}_{i,t}$	0.00885	0.0122	0.00967	0.0141	0.0130	0.0294	0.00202	0.0129
	(0.0307)	(0.0238)	(0.0347)	(0.0267)	(0.0401)	(0.0291)	(0.0353)	(0.0297)
$logy_{i,t-1}$	-0.0360	-0.0141	-0.0507	-0.0513	0.0122	-0.0756	-0.0385	-0.0340
	(0.0489)	(0.0535)	(0.0541)	(0.0540)	(0.0967)	(0.0658)	(0.0456)	(0.0417)
$\Delta logh_{i,t-1}$	0.0225	0.327	-0.385	-0.212	0.00715	-0.00515	-0.187	1.328
	(0.871)	(0.932)	(0.890)	(0.721)	(0.826)	(0.952)	(0.817)	(1.406)
$logk_{i,t-1}$	0.00518	-0.0117	0.0112	0.0134	-0.0212	0.0227	0.00614	0.00736
	(0.0266)	(0.0364)	(0.0311)	(0.0319)	(0.0549)	(0.0331)	(0.0224)	(0.0234)
$logai^{APP}_{i,t-1}$	-0.00504	-0.00453	-0.00526	-0.00440	-0.00966	-0.00329	-0.00428	-0.00563
	(0.00896)	(0.00946)	(0.00799)	(0.00995)	(0.0115)	(0.00829)	(0.00876)	(0.00619)
$loginn^{APP}_{i,t-1}$	0.00722	0.00889	0.00882	0.00708	0.00774	0.00885	0.00604	0.00956
	(0.00838)	(0.00769)	(0.00717)	(0.00753)	(0.00671)	(0.00851)	(0.00843)	(0.00790)
$\Delta trade_{i,t}$		0.00272***						
		(0.000593)						
$\Delta rqe_{i,t}$			-0.00835					
			(0.0273)					
$\Delta inds_{i,t}$				0.0112				
				(0.0151)				
$\Delta g_{i,t}$					-0.0282			
					(0.0198)			
$\Delta inf_{i,t}$						0.00431		
						(0.00338)		
$\Delta fdi_{i,t}$							-0.000075	
							(0.000676)	
$\Delta urban_{i,t}$								-0.0739
								(0.0634)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Observations	714	714	714	714	714	714	714	714
No. of Countries	34	34	34	34	34	34	34	34
No. of instruments	30	30	30	30	30	30	30	30
AR1 (p-value)	0.000	0.001	0.000	0.001	0.002	0.001	0.000	0.000
AR2 (p-value)	0.091	0.723	0.085	0.167	0.602	0.405	0.151	0.092
Hansen-J	27.923	20.607	25.083	25.729	28.137	28.987	25.374	23.904
Hansen-J (p-value)	0.111	0.359	0.158	0.138	0.081	0.066	0.149	0.200
BIC	-4373.548	-4438.911	-4343.215	-4408.075	-4586.347	-4358.672	-4366.859	-4275.090

Notes: robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Table 11. Results with Diff-GMM and additional control variables – ai^{INV}

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta^2 logh_{i,t}$	2.890*	1.712	2.671*	1.527	-0.0423	3.016*	3.767**	2.941*
	(1.511)	(1.734)	(1.553)	(1.575)	(1.340)	(1.786)	(1.520)	(1.582)
$\Delta logk_{i,t}$	0.151*	0.117*	0.141*	0.176***	0.0896	0.135	0.172**	0.146***
	(0.0775)	(0.0708)	(0.0748)	(0.0661)	(0.0720)	(0.0850)	(0.0726)	(0.0545)
$\Delta logai^{INV}_{i,t}$	0.0547**	0.0416*	0.0491**	0.0352*	0.0228	0.0452*	0.0632**	0.0536***
	(0.0259)	(0.0214)	(0.0247)	(0.0213)	(0.0180)	(0.0263)	(0.0292)	(0.0173)
$\Delta loginn^{INV}_{i,t}$	0.109	0.0627	0.117*	0.106*	0.0968**	0.105	0.108	0.142*
	(0.0718)	(0.0603)	(0.0690)	(0.0556)	(0.0459)	(0.0659)	(0.0821)	(0.0776)
$logy_{i,t\text{-}1}$	-0.592***	-0.541**	-0.585***	-0.541***	-0.347**	-0.576***	-0.607***	-0.678***
	(0.202)	(0.211)	(0.213)	(0.191)	(0.161)	(0.168)	(0.216)	(0.257)
$\Delta logh_{i,t\text{-}1}$	0.814	0.236	0.858	0.340	-1.606	0.682	0.443	0.785
	(1.765)	(1.514)	(1.902)	(1.912)	(1.500)	(1.747)	(1.666)	(2.171)
$logk_{i,t\text{-}1}$	0.111*	0.0919	0.109*	0.0972	0.0416	0.115**	0.103	0.140*
	(0.0637)	(0.0571)	(0.0639)	(0.0648)	(0.0563)	(0.0569)	(0.0691)	(0.0850)
$logai^{INV}_{i,t\text{-}1}$	0.0584***	0.0443**	0.0537***	0.0420*	0.0252	0.0488**	0.0643***	0.0578***
	(0.0193)	(0.0183)	(0.0200)	(0.0222)	(0.0166)	(0.0217)	(0.0212)	(0.0183)
$loginn^{INV}_{i,t\text{-}1}$	0.117*	0.116	0.117*	0.124**	0.0974**	0.109*	0.117	0.140*
	(0.0693)	(0.0777)	(0.0689)	(0.0573)	(0.0385)	(0.0602)	(0.0715)	(0.0788)
$\Delta trade_{i,t}$		0.00199**						
		(0.000872)						

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta rqe_{i,t}$			0.00507					
			(0.0207)					
$\Delta inds_{i,t}$				0.0182*				
				(0.0108)				
$\Delta g_{i,t}$					-0.038***			
					(0.0104)			
$\Delta inf_{i,t}$						0.00413		
						(0.00573)		
$\Delta fdi_{i,t}$							-0.00107	
							(0.00108)	
$\Delta urban_{i,t}$								0.0228
								(0.212)
Observations	680	680	680	680	680	680	680	680
No. of Countries	34	34	34	34	34	34	34	34
No. of instruments	24	24	24	24	24	24	24	24
AR1 (p-value)	0.073	0.088	0.054	0.044	0.008	0.062	0.072	0.105
AR2 (p-value)	0.238	0.516	0.295	0.298	0.555	0.626	0.337	0.345
Hansen-J	19.279	18.419	18.468	19.632	13.883	17.463	18.350	15.452
Hansen-J (p-value)	0.201	0.188	0.186	0.142	0.458	0.232	0.191	0.348
BIC	1919.975	1826.340	1904.225	1789.356	1270.474	1871.554	1997.590	2052.225

Notes: robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Table 12. Results with Sys-GMM and additional control variables – ai^{INV}

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta^2 logh_{i,t}$	0.168	-0.721	0.130	0.0908	-0.232	1.660	1.223	0.404
	(1.307)	(1.331)	(1.377)	(1.337)	(1.594)	(1.339)	(1.227)	(1.087)
$\Delta logk_{i,t}$	0.132	0.122	0.143	0.158**	0.121	0.159**	0.166*	0.156**
	(0.0925)	(0.0954)	(0.0966)	(0.0752)	(0.0833)	(0.0808)	(0.0862)	(0.0783)
$\Delta logai^{INV}_{i,t}$	0.00363	0.00259	0.00242	0.00340	-0.00185	0.0122	0.0181	-0.00502
	(0.0157)	(0.0131)	(0.0138)	(0.0106)	(0.0164)	(0.0153)	(0.0238)	(0.0172)
$\Delta loginn^{INV}_{i,t}$	-0.0130	-0.0612*	-0.0128	-0.00318	-0.00618	-0.0129	-0.000280	-0.0197
	(0.0328)	(0.0321)	(0.0334)	(0.0420)	(0.0345)	(0.0263)	(0.0369)	(0.0250)
$logy_{i,t-1}$	-0.0721	-0.0152	-0.0755	-0.0430	0.0148	-0.0928	-0.0952*	-0.0547
	(0.0490)	(0.0546)	(0.0537)	(0.0628)	(0.0661)	(0.0590)	(0.0544)	(0.0539)
$\Delta logh_{i,t-1}$	-0.0672	-0.0954	-0.174	-0.305	-0.585	-0.109	-0.192	0.679
	(0.857)	(0.823)	(0.935)	(0.842)	(0.756)	(1.080)	(0.923)	(1.679)
$logk_{i,t-1}$	0.0314	-0.00867	0.0322	0.0106	-0.0194	0.0301	0.0393	0.0143
	(0.0284)	(0.0351)	(0.0320)	(0.0399)	(0.0355)	(0.0330)	(0.0295)	(0.0260)
$logai^{INV}_{i,t-1}$	-0.00164	-0.00195	-0.00203	-0.000962	-0.00633	0.000973	0.00484	-0.00466
	(0.0110)	(0.00948)	(0.0102)	(0.00920)	(0.0117)	(0.0108)	(0.0142)	(0.0128)
$loginn^{INV}_{i,t-1}$	0.00385	0.00202	0.00484	0.00296	0.00150	0.00427	0.00229	0.00915
	(0.00730)	(0.00664)	(0.00707)	(0.00772)	(0.00764)	(0.00843)	(0.00875)	(0.00804)
$\Delta trade_{i,t}$		0.00306**						
		(0.00129)						
$\Delta rqe_{i,t}$			0.00477					
			(0.0171)					
$\Delta inds_{i,t}$				0.0192				
				(0.0163)				
$\Delta g_{i,t}$					-0.0340**			
					(0.0140)			
$\Delta inf_{i,t}$						0.00718***		
						(0.00228)		
$\Delta fdi_{i,t}$							-0.00113	
							(0.000943)	
$\Delta urban_{i,t}$								-0.0542
								(0.125)
Observations	714	714	714	714	714	714	714	714

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No. of Countries	34	34	34	34	34	34	34	34
No. of instruments	30	30	30	30	30	30	30	30
AR1 (p-value)	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001
AR2 (p-value)	0.073	0.392	0.082	0.200	0.516	0.278	0.100	0.072
Hansen-J	30.189	26.306	29.319	27.696	29.366	29.503	28.094	27.966
Hansen-J (p-value)	0.067	0.122	0.061	0.089	0.060	0.058	0.082	0.084
BIC	-4332.376	-4412.179	-4320.102	-4398.874	-4576.881	-4310.827	-4215.965	-4285.112

Notes: robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Table 13. Results with Diff-GMM and additional control variables – ai^{PUB}

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta^2 logh_{i,t}$	0.371	1.139	0.0379	-0.671	0.382	2.051	0.186	0.442
	(1.941)	(1.639)	(2.155)	(1.663)	(1.795)	(2.324)	(1.875)	(1.462)
$\Delta logk_{i,t}$	0.0621	0.0816	0.0791	0.0954**	0.0904	0.00798	0.0567	0.0709
	(0.0668)	(0.0535)	(0.0798)	(0.0417)	(0.0617)	(0.0668)	(0.0668)	(0.0671)
$\Delta logai^{PUB}_{i,t}$	0.0188	0.000496	0.0195	0.0370*	0.0222	0.0128	0.0203	0.00836
	(0.0275)	(0.0257)	(0.0306)	(0.0195)	(0.0161)	(0.0248)	(0.0268)	(0.0505)
$\Delta loginn^{PUB}_{i,t}$	0.00295	0.0228	-0.00165	-0.0340	-0.0138	0.0214	0.00776	0.0190
	(0.0426)	(0.0348)	(0.0447)	(0.0334)	(0.0256)	(0.0398)	(0.0423)	(0.0799)
$logy_{i,t-1}$	0.0908	0.0410	0.0946	0.0894	0.107*	0.0437	0.0740	0.0390
	(0.0726)	(0.0613)	(0.0926)	(0.0553)	(0.0618)	(0.0952)	(0.0732)	(0.0791)
$\Delta logh_{i,t-1}$	-0.180	0.287	-0.270	-0.681	0.357	0.591	0.283	0.387
	(1.556)	(1.402)	(1.703)	(1.673)	(1.321)	(1.804)	(1.539)	(1.664)
$logk_{i,t-1}$	-0.104**	-0.0559	-0.103**	-0.0953**	-0.099***	-0.118*	-0.096**	-0.0689
	(0.0525)	(0.0409)	(0.0502)	(0.0373)	(0.0368)	(0.0622)	(0.0488)	(0.0525)
$logai^{PUB}_{i,t-1}$	-0.00887	-0.00680	-0.00848	0.00767	-0.000282	-0.00566	-0.00944	-0.00427
	(0.0214)	(0.0175)	(0.0227)	(0.0161)	(0.0142)	(0.0198)	(0.0225)	(0.0355)
$loginn^{PUB}_{i,t-1}$	0.0208	0.0139	0.0192	-0.00628	0.000839	0.0353	0.0288	0.0123
	(0.0311)	(0.0227)	(0.0300)	(0.0214)	(0.0209)	(0.0280)	(0.0380)	(0.0532)
$\Delta trade_{i,t}$		0.00257***						
		(0.000815)						

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta rqe_{i,t}$			0.0153					
			(0.0399)					
$\Delta inds_{i,t}$				0.0291***				
				(0.00732)				
$\Delta g_{i,t}$					-0.034***			
					(0.0105)			
$\Delta inf_{i,t}$						0.00815***		
						(0.00291)		
$\Delta fdi_{i,t}$							0.000850	
							(0.00129)	
$\Delta urban_{i,t}$								0.241
								(0.251)
Observations	680	680	680	680	680	680	680	680
No. of Countries	34	34	34	34	34	34	34	34
No. of instruments	24	24	24	24	24	24	24	24
AR1 (p-value)	0.001	0.001	0.002	0.001	0.002	0.001	0.008	0.002
AR2 (p-value)	0.216	0.650	0.270	0.276	0.614	0.359	0.627	0.184
Hansen-J	20.269	11.562	18.709	12.072	12.824	14.569	19.455	23.626
Hansen-J (p-value)	0.162	0.641	0.176	0.601	0.540	0.408	0.148	0.051
BIC	-2519.428	-2528.241	-2835.680	-1869.963	-3433.720	-575.648	-2476.49	-1646.936

Notes: robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Table 14. Results with Sys-GMM and additional control variables – ai^{PUB}

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta^2 logh_{i,t}$	0.158	0.495	-0.255	0.0159	0.256	1.276	0.114	-0.746
	(1.172)	(1.230)	(1.700)	(1.210)	(1.285)	(1.066)	(1.357)	(1.318)
$\Delta logk_{i,t}$	0.124*	0.138**	0.121*	0.121**	0.112	0.0889*	0.125	0.128**
	(0.0659)	(0.0694)	(0.0668)	(0.0604)	(0.0853)	(0.0518)	(0.0792)	(0.0587)
$\Delta logai^{PUB}_{i,t}$	0.0215	0.0218	0.0235	0.0280*	0.0187*	0.00786	0.0258	0.0135
	(0.0136)	(0.0133)	(0.0163)	(0.0151)	(0.0112)	(0.0138)	(0.0198)	(0.0158)
$\Delta loginn^{PUB}_{i,t}$	-0.0120	-0.0206	-0.0135	-0.0218	-0.0145	0.00471	-0.0160	-0.00118
	(0.0219)	(0.0206)	(0.0280)	(0.0261)	(0.0174)	(0.0202)	(0.0269)	(0.0248)
$logy_{i,t-1}$	-0.0208	0.0112	-0.0125	0.0111	0.0644	-0.0208	-0.0146	-0.0278
	(0.0415)	(0.0351)	(0.0363)	(0.0560)	(0.0789)	(0.0310)	(0.0449)	(0.0408)
$\Delta logh_{i,t-1}$	-0.642	-0.814	-0.744	-0.429	0.0713	0.356	-0.490	-1.920
	(1.092)	(1.000)	(1.361)	(0.896)	(1.439)	(1.059)	(1.196)	(1.502)
$logk_{i,t-1}$	0.00158	-0.0148	-0.00377	-0.0198	-0.0502	-0.00614	-0.00209	-0.00200
	(0.0244)	(0.0236)	(0.0225)	(0.0353)	(0.0526)	(0.0206)	(0.0255)	(0.0251)
$logai^{PUB}_{i,t-1}$	0.00886	0.00931	0.0127	0.0122	0.00804	0.00104	0.0109	-0.00136
	(0.0118)	(0.0100)	(0.0155)	(0.0142)	(0.00970)	(0.0141)	(0.0119)	(0.0140)
$loginn^{PUB}_{i,t-1}$	-0.0108	-0.0161	-0.0151	-0.0153	-0.0143	0.00104	-0.0124	0.00389
	(0.0151)	(0.0127)	(0.0198)	(0.0177)	(0.0117)	(0.0177)	(0.0155)	(0.0174)
$\Delta trade_{i,t}$		0.00256***						
		(0.000583)						
$\Delta rqe_{i,t}$			0.0336					
			(0.0425)					
$\Delta inds_{i,t}$				0.0122				
				(0.0150)				
$\Delta g_{i,t}$					-0.0347**			
					(0.0165)			
$\Delta inf_{i,t}$						0.00642**		
						(0.00257)		
$\Delta fdi_{i,t}$							0.000494	
							(0.00102)	
$\Delta urban_{i,t}$								0.111**
								(0.0554)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Observations	714	714	714	714	714	714	714	714
No. of Countries	34	34	34	34	34	34	34	34
No. of instruments	30	30	30	30	30	30	30	30
AR1 (p-value)	0.000	0.001	0.001	0.001	0.002	0.000	0.003	0.001
AR2 (p-value)	0.161	0.667	0.279	0.223	0.593	0.270	0.414	0.159
Hansen-J	26.978	20.411	27.971	25.292	23.300	23.576	26.511	22.628
Hansen-J (p-value)	0.136	0.370	0.084	0.151	0.224	0.213	0.117	0.254
BIC	-4378.942	-4432.491	-4362.254	-4431.002	-4533.846	-4411.335	-4361.146	-4087.719

Notes: robust standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.010$.

3.2.3. *Alternative AI adoption measures: stocks*

Given the cumulative nature of knowledge and technology, a case can be made for considering our patent and publication variables in terms of stocks instead of a yearly flow. We thus estimated our baseline model using the stocks of the three AI proxies, also retrieved from Parteka & Kordalska (2023), which the authors compute using the flows and applying the perpetual inventory method. Using the stocks of the AI variables we had to remove Latvia from our sample for which no data is available. As can be seen from the inspection of Table 15, there are some interesting differences in the results, despite the overall effect of AI metrics on growth remaining positive in most cases. The results using the stocks of AI patents lead to a loss of statistical significance of the short-run effects while the long-run effect remains unchanged, positive and statistically significant (with Diff-GMM). On the other hand, AI related publications now display positive and statistically significant estimated coefficients in the short and long-run (with Diff-GMM).

Table 15. Results using AI stock variables

	Diff-GMM			Sys-GMM		
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation/AI	*APP*	*INV*	*PUB*	*APP*	*INV*	*PUB*
$\Delta^2 logh_{i,t}$	1.942	1.026	0.890	0.899	1.355	0.0551
	(1.633)	(0.917)	(1.280)	(1.433)	(1.337)	(2.522)
$\Delta logk_{i,t}$	0.173***	0.152**	0.111	0.189***	0.196***	0.154**
	(0.0584)	(0.0680)	(0.0786)	(0.0705)	(0.0619)	(0.0638)
$\Delta logai^{APP}_{i,t}$	0.104			0.0243		
	(0.112)			(0.0282)		
$\Delta loginn^{APP}_{i,t}$	0.791***			0.112		
	(0.234)			(0.120)		
$logy_{i,t-1}$	-0.727***	-0.575***	-0.422***	-0.113**	-0.122**	-0.0419
	(0.135)	(0.103)	(0.0805)	(0.0503)	(0.0519)	(0.0344)
$\Delta logh_{i,t-1}$	0.176	-1.303	1.627	-0.342	0.761	-0.168
	(1.382)	(1.323)	(1.897)	(1.180)	(1.840)	(1.735)
$logk_{i,t-1}$	0.135***	0.119***	0.0597	0.0560*	0.0594**	0.0196
	(0.0403)	(0.0287)	(0.0366)	(0.0294)	(0.0277)	(0.0218)
$logai^{APP}_{i,t-1}$	0.0691**			-0.00409		
	(0.0279)			(0.00604)		
$loginn^{APP}_{i,t-1}$	0.153***			0.00872		
	(0.0335)			(0.00545)		
$\Delta logai^{INV}_{i,t}$		0.0696			0.0757	
		(0.0642)			(0.0643)	
$logai^{INV}_{i,t-1}$		0.0364*			0.00339	
		(0.0187)			(0.00728)	
$\Delta loginn^{INV}_{i,t}$		0.635***			0.132	
		(0.211)			(0.119)	
$loginn^{INV}_{i,t-1}$		0.117***			0.00784	
		(0.0324)			(0.00716)	
$\Delta logai^{PUB}_{i,t}$			0.228***			0.195***
			(0.0733)			(0.0503)

	Diff-GMM			Sys-GMM		
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation/AI	*APP*	*INV*	*PUB*	*APP*	*INV*	*PUB*
$logai^{PUB}_{i,t-1}$			0.128***			0.00647
			(0.0401)			(0.0180)
$\Delta loginn^{PUB}_{i,t}$			-0.201			-0.313*
			(0.219)			(0.168)
$loginn^{PUB}_{i,t-1}$			-0.0960*			-0.00730
			(0.0528)			(0.0211)
Observations	680	680	680	714	714	714
No. of Countries	34	34	34	34	34	34
No. of instruments	34	34	34	40	40	40
AR1 (p-value)	0.0447	0.0128	0.0028	0.0010	0.0021	0.0007
AR2 (p-value)	0.253	0.283	0.167	0.121	0.166	0.0800
Hansen-J	30.74	32.08	33.18	29.40	30.92	32.90
Hansen-J (p-value)	0.198	0.156	0.127	0.497	0.419	0.327

Notes: obust Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010

3.2.4. *Coefficient stability*

The stability over time of the estimated coefficients is a key concern when working with panel data. In our study, the importance of this issue is heightened by the evolving discourse surrounding AI in recent years. Although automation, robotisation, and AI have been long-standing topics of interest, the significant breakthroughs observed in recent years are likely to cause notable shifts in economic behaviour. To assess the robustness of our results, we re-estimate the model over successive time windows – starting with the period 1995-2005 and incrementally adding one year at a time. Figures 2-3 illustrate how the estimated coefficients of interest – those related to AI, general innovation, and the model's error correction term – evolve in this recursive estimation process. To conserve space, we present here only the results from the models using patents by applicant. The remaining results are available upon request. Our findings indicate that the coefficients remain largely stable as the time window expands when using the patents measures; however, some variability is observed when using the scientific publications measure (these results are available from the authors).

Figure 2. Diff-GMM estimated coefficients over expanding windows (ai^{APP}; inn^{APP})

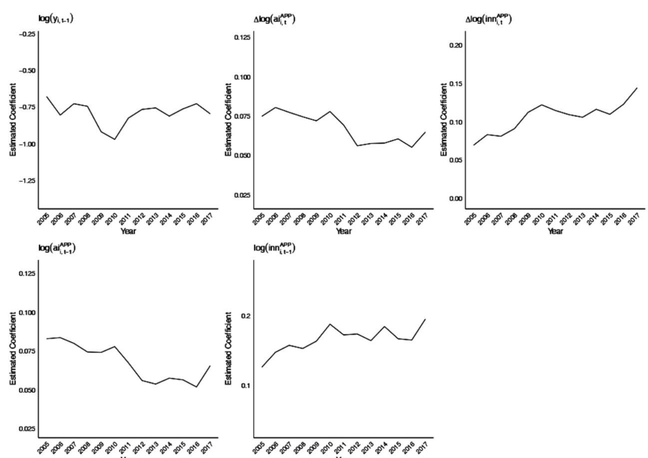
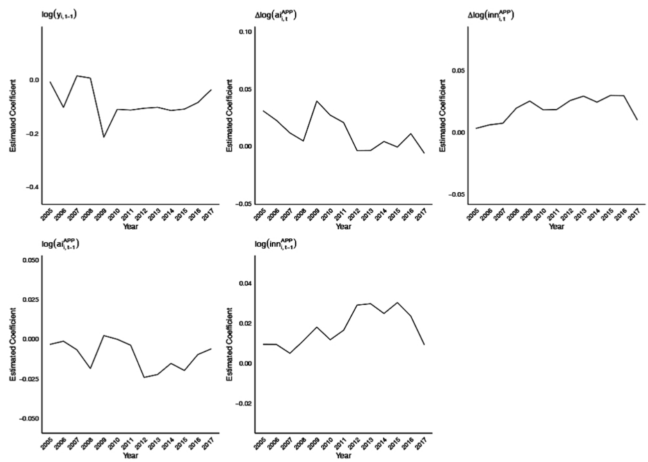


Figure 3. Sys-GMM estimated coefficients over expanding windows (*ai*^{APP}; *inn*^{APP})



Despite the overall stability suggested by the results in Figures 2 and 3, a slight downward trend can be observed in the estimated coefficients of AI, particularly in the Diff-GMM results shown in Figure 2. Since these estimates are based on flow measures of AI, one possible explanation is that, as the stock of AI accumulates over time, the marginal impact of new patents and scientific publications decreases, reflecting potential diminishing returns. To examine this possibility, we replicated the coefficient stability analysis using stock-based AI variables (see Figures 4 and 5). The results confirm that the previously observed downward trend in the estimated AI coefficients is much less pronounced.

Figure 4. Diff-GMM estimated coefficients over expanding windows (*ai*^{APP}; *inn*^{APP}) – stock variables

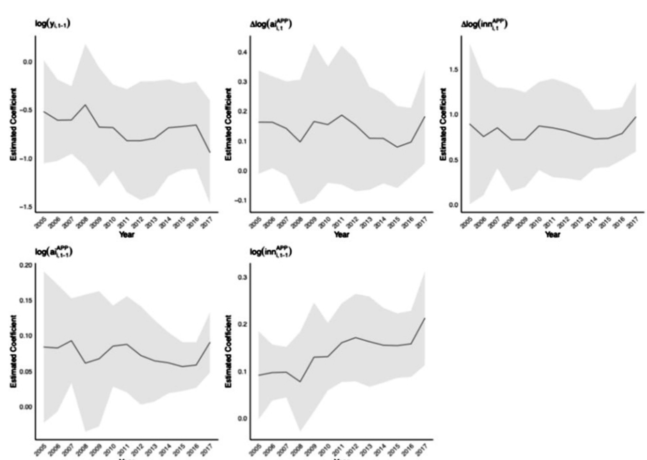
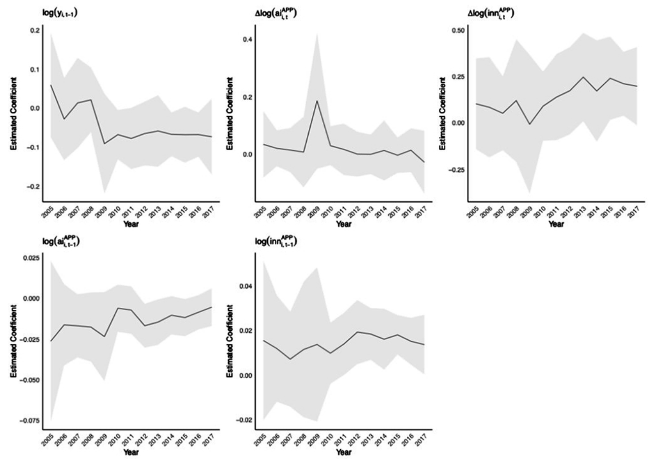


Figure 5. Sys-GMM estimated coefficients over expanding windows (ai^{APP}; inn^{APP}) – stock variables



3.3. The role of human capital

In this section we extend the analysis to account for the role of human capital by including an interaction term between AI and human capital. This enables us to assess whether the growth effects of AI differ across countries with varying skill endowments, shedding light on whether AI acts as a complement or substitute to human capabilities in the aggregate in line with the approaches developed by, among others, Autor (2015) and Acemoglu & Restrepo (2019), and recently tested using microdata by Bughin (2025) and Brynjolfsson, Li, & Raymond (2025). The long-run relationship is now given by equation (5):

$$\log y_{i,t} = \alpha_{0,i} + \alpha_1 \log k i,t + \alpha_2 \Delta \log h_{i,t} + \alpha_3 \log ai_{i,t} + \alpha_4 \log inn_{i,t} + \alpha_5 \log h_{i,t} \times \log ai_{i,t} + \quad + \varepsilon_{i,t} \qquad (5)$$

where we augment equation (3) to include $logh_{i,t}$ x $logai_{i,t}$, the interaction term between AI and human capital, with the sign of the respective estimated coefficient indicating whether human capital amplifies or dampens the AI effect. A positive estimated coefficient for AI combined with an also positive estimated coefficient for the interaction term suggests complementarity, i.e. AI raises productivity and thus growth more where human capital is higher, in line with the literature that poses that AI is skill-biased in favour of more advanced skills, see e.g. Acemoglu & Restrepo (2019), with the scope of human-machine collaboration with AI greater for high-skilled workers. Thus, technology complementarity favours highly skilled workers at the expense of lower-skilled workers that perform less cognitive and more repetitive tasks. On the contrary, a positive estimated coefficient for AI combined with a negative estimated coefficient for the interaction term indicates that AI increases productivity and output overall but less so where human capital is higher, in other words producing relatively larger marginal gains at lower human-capital levels. The latter is consistent with the customer service firm microdata results obtained by Brynjolfsson, Li, & Raymond (2025) according to which the workers that benefit most from AI shocks associated with the introduction and spread of the more recent large language models (LLMs) proxied by generative AI–based conversational assistants are the lower-skilled workers for whom AI assistance disproportionately facilitates learning.

We first performed panel cointegration tests for the long-run relationship described by equation (5) using the procedure proposed by Westerlund (2005), see Table 16, considering the two versions of the test. The first, with the alternative hypothesis that only some of the cross-sectional units display cointegration and the second version considering as the alternative hypothesis the possibility that all the panel units display cointegration. In both cases, we perform the test with and without a trend in the model. The results provide evidence in favour of the existence of cointegration among the variables included in the long-run regression given by equation (5) when we consider a trend in the model.

Table 16. Results of the Westerlund (2005) panel cointegration tests

		No Trend	**With Trend**
APP	All Panels	0.1949	0.0339
	Some Panels	0.3109	0.0000
INV	All Panels	0.3367	0.0028
	Some Panels	0.4851	0.0000
PUB	All Panels	0.4763	0.0000
	Some Panels	0.3301	0.0000

Notes: the table contains the p-values for the Westerlund panel cointegration test Westerlund (2005). The null of the test is the absence of cointegration among the series.

Table 17 reports the findings of estimating the ARDL with the introduction in the long-run relationship of the interaction term between AI and human capital considering our three proxies of AI adoption and both Diff-GMM and Sys-GMM estimators. Taken together, the results do not seem to endorse a relevant role for human capital in the aggregate and for the period considered as most of the estimated coefficients for the interaction terms are not statistically significant (nine out of twelve). Additionally, the statistically significant results lead to quite different interpretations concerning the role of human capital depending on the AI proxy used. With AI patents data (columns (4) and (5)), the results support that in the short-run AI leads to larger marginal gains at lower human-capital levels. On the contrary, using AI scientific publications points to AI being skill-biased in the long-run (column (3)). Based on these results with aggregate data, it is does not seem possible to have a clear picture about of what type of labour is benefitting more from AI advancements. In any case, at the more disaggregate industry or firm-level studies point to disproportionate gains to either high or low-skilled workers depending on the specific sectors/firms under analysis and these opposite sign effects can cancel out when using aggregate data.

Table 17. Results including an interaction term between AI and human capital

	Diff-GMM			Sys-GMM		
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation/AI	*APP*	*INV*	*PUB*	*APP*	*INV*	*PUB*
$\Delta^2 logh_{i,t}$	3.054	0.822	0.917	-1.163	-0.396	-1.200
	(1.946)	(1.534)	(1.198)	(2.150)	(1.506)	(2.196)
$\Delta logk_{i,t}$	0.185***	0.113	0.0282	0.139*	0.115	0.150***
	(0.0545)	(0.0726)	(0.0398)	(0.0759)	(0.0866)	(0.0497)
$\Delta logai^{APP}_{i,t}$	-0.122			0.452*		
	(0.179)			(0.265)		
$\Delta loginn^{APP}_{i,t}$	0.152***			0.00574		
	(0.0343)			(0.0270)		
$logy_{i,t-1}$	-0.765***	-0.569***	0.0879	-0.118	-0.119**	-0.0623
	(0.198)	(0.135)	(0.0683)	(0.0726)	(0.0557)	(0.0450)
$\Delta logh_{i,t-1}$	1.958	-0.920	0.223	-0.423	-1.144	-3.500
	(1.619)	(1.770)	(0.834)	(1.904)	(1.200)	(2.910)
$logk_{i,t-1}$	0.145**	0.0880*	-0.209***	0.0470	0.0598	0.0358
	(0.0734)	(0.0465)	(0.0547)	(0.0465)	(0.0369)	(0.0290)
$logai^{APP}_{i,t-1}$	-0.113			0.00846		
	(0.125)			(0.106)		
$loginn^{APP}_{i,t-1}$	0.202***			0.0164		
	(0.0407)			(0.0106)		
$logh_{i,t}$ x $\Delta logai^{APP}_{i,t}$	0.140			-0.393*		
	(0.152)			(0.221)		
$logh_{i,t}$ x $logai^{APP}_{i,t-1}$	0.137			-0.0125		
	(0.0939)			(0.0770)		
$\Delta logai^{INV}_{i,t}$		0.259			0.499*	
		(0.286)			(0.259)	
$logai^{INV}_{i,t-1}$		-0.0772			0.0358	
		(0.140)			(0.0856)	
$\Delta loginn^{INV}_{i,t}$		0.125**			0.00401	
		(0.0488)			(0.0351)	

	Diff-GMM			Sys-GMM		
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation/AI	*APP*	*INV*	*PUB*	*APP*	*INV*	*PUB*
$loginn^{INV}_{i,t-1}$		0.149***			0.00637	
		(0.0499)			(0.0113)	
$logh_{i,t}$ x $\Delta logai^{INV}_{i,t}$		-0.201			-0.425**	
		(0.236)			(0.212)	
$logh_{i,t}$ x $logai^{INV}_{i,t-1}$		0.0999			-0.0267	
		(0.109)			(0.0600)	
$\Delta logai^{PUB}_{i,t}$			-0.0697			0.0647
			(0.142)			(0.0781)
$logai^{PUB}_{i,t-1}$			-0.173***			0.0357
			(0.0461)			(0.0395)
$\Delta loginn^{PUB}_{i,t}$			0.0841***			-0.0196
			(0.0263)			(0.0207)
$loginn^{PUB}_{i,t-1}$			0.112***			-0.0124
			(0.0383)			(0.0137)
$logh_{i,t}$ x $logai^{PUB}_{i,t}$			0.0384			-0.0359
			(0.121)			(0.0622)
$logh_{i,t}$ x $ogai^{PUB}_{i,t-1}$			0.108***			-0.0219
			(0.0341)			(0.0264)
Observations	700	700	700	735	735	735
No. of Countries	35	35	35	35	35	35
No. of instruments	24	24	24	30	30	30
AR1 (p-value)	0.458	0.0146	0.0011	0.0035	0.0007	0.0004
AR2 (p-value)	0.293	0.113	0.142	0.831	0.557	0.111
Hansen-J	7.360	14.13	8.594	21.46	19.45	23.54
Hansen-J (p-value)	0.833	0.365	0.803	0.206	0.303	0.171

Notes: the results presented in columns (1), (4) and (5) include the first lag of the dependent variable to deal with the rejection of the AR2 test. Robust Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

4. Conclusion

It is widely accepted that technological progress underpins economic growth. This paper delved into the effects of AI adoption, a recent and promising form of technological progress, on economic growth and standards of living across a sample of 35 OECD countries over a little more than two decades, from 1995 to 2017. Panel autoregressive distributed lag (ARDL) models were employed to evaluate the long-run relationship and short-run impacts of AI adoption proxied by AI patents by applicants or inventors and AI-related scientific publications. While AI adoption may fluctuate in the short run, it could tend to correlate more consistently with real GDP per capita over the long run. It is therefore important to assess whether there is an enduring connection between these variables, distinguishing it from the short-run fluctuations. The prospect of skill-biased technological change in the context of AI, which may favour highly skilled workers while displacing those performing routine manual tasks, raises concerns about wage and employment polarisation. However, recent developments in generative AI suggest potential benefits for lower-skilled workers. Examining the nonlinear interaction between AI and human capital can help shed some light on these effects from a broader macroeconomic perspective.

Using patent data and a first-differenced GMM approach, our preferred results indicate that AI adoption is already fostering short-term economic growth and, over time, contributing to higher living standards. However, these effects are not uniform across all settings. When examining human capital, these aggregate results reveal no clear advantage for any particular group of workers. Capitalising on the AI potential advises putting in place policies that tackle obstacles and challenges such as providing the necessary infrastructure, addressing skills shortages or prioritising governance, transparency and AI ethics. As Autor (2022), p. 26 writes '(…) absent complementary institutional investments, technological innovation alone will not generate broadly shared gains.' He also explains where he thinks these institutional investments should concentrate: education and training, labor market institutions, and innovation policy.

As each new wave of AI is anticipated to have a growing impact on the economy, our estimates should be considered a lower bound that advises continuing monitoring of the effects of AI on economic growth and standards of living, bearing in mind that the associated increases in real GDP per capita do not necessarily imply shared prosperity. If and when artificial general intelligence (AGI) becomes a reality, i.e. artificial intelligence that 'possesses the ability to understand, learn, and perform any intellectual task a human being can perform' Korinek (2023), p. 31, even though the benefits in terms of growth and standards of living may accelerate, real GDP per capita is just an average, not accounting for income distribution. It is thus possible to envisage a scenario where AGI leads to massive job losses and unemployment, instead of primarily complementing human work, and widening income inequality will follow threatening future wellbeing, Autor (2022). To address this question, future research could tackle both effects simultaneously by e.g. estimating adequate models to account for the interactions and feedback effects between AI adoption, economic growth and inequality. Another important consideration is that, at the micro and sectoral levels, AI can enhance productivity by substituting for certain skill sets while complementing others. However, these heterogeneous effects may be obscured in aggregate analyses, underscoring the need for more disaggregated studies.

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Measuring Efficiency and Productivity Change of Insurance Companies in the European Union

Avaliação da Evolução da Eficiência e da Produtividade das Companhias de Seguros na União Europeia

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ABSTRACT
This article analyses the efficiency of European insurance companies (composite, life and non-life) in 27 EU countries over the period 2014–2023. Using Data Envelopment Analysis and the Malmquist index, the study examines the impact of technological change and input–output management. The results reveal efficiency differences between countries and positive productivity trends in most of them. Life insurers were the most efficient, although their efficiency declined during 2021–2022. Composite insurers were less efficient than life and non-life insurers, the latter of which significantly improved their performance in 2022–2023. Overall, efficiency growth depends both on process improvements and on technological innovations.
Keywords: insurance efficiency, life insurer, non-life insurer, composite insurer, technological innovation

JEL Codes: G22

RESUMO
Este artigo analisa a eficiência das empresas de seguros europeias (compostas, de vida e não vida) em 27 países da UE durante o período de 2014-2023. Recorrendo ao método Data

Envelopment Analysis e ao índice de Malmquist, o estudo examina o impacto da mudança tecnológica e da gestão dos inputs e outputs. Os resultados revelam diferenças de eficiência entre países e tendências positivas de produtividade na maioria deles. As seguradoras de vida são as mais eficientes, embora a sua eficiência tenha diminuído em 2021-2022. As seguradoras compostas apresentaram menor eficiência do que as seguradoras de vida e não vida, sendo que estas últimas melhoraram significativamente o seu desempenho em 2022-2023. Em geral, o crescimento da eficiência depende tanto das melhorias nos processos como das inovações tecnológicas.

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1. Introduction

The insurance market represents a vital part of the economy, with its growth significantly influencing a nation's economic progress. The insurance industry plays a crucial role in the stability and growth of the economy. It contributes to growth of the real economy and helps maintain financial stability by reducing the impact of losses on businesses and households through risk-sharing (Časta et al. 2021). In the European Union (EU), where the insurance market is both diverse and highly regulated, understanding the efficiency of insurers is essential for ensuring competitiveness, resilience, and sustainable growth. This need has become even more pronounced in the wake of the COVID-19 pandemic, which has accelerated digital transformation and reshaped operational dynamics within the industry.

The COVID-19 pandemic has accelerated the digital transformation of insurance companies, turning it from a strategic choice to an essential requirement. Before the pandemic, the insurance industry lagged behind the banking sector in adopting digital technologies (Puschmann 2017; Stoeckli et al. 2018). Today, rapid changes are reshaping the insurance sector. Companies are adopting measures to become more customer-focused, improve their offerings, and boost efficiency (Pauch and Bera 2022).

Despite this growing importance, there is still a limited number of empirical studies analysing how digital transformation and technological change affect the efficiency of insurance companies across the European Union. Most previous research has focused on individual markets or on the period before the pandemic, leaving a research gap in understanding post-pandemic efficiency dynamics. Moreover, existing studies rarely compare different types of insurers (life, non-life, and composite) within a single analytical framework, which limits insights into how specialization influences performance.

This study therefore aims to fill this gap by providing an updated, EU-wide assessment of insurers' efficiency and productivity in the context of accelerating digital transformation. Specifically, it conducts a comparative efficiency analysis of 1,823 insurance companies operating in 27 EU countries over the period 2014–2023. By applying the Data Envelopment Analysis (DEA) and the Malmquist index, the study aims to capture both efficiency and productivity changes in the context of technological progress and digital transformation.

Based on the literature review and the identified research gap, this paper formulates two main hypotheses. First, technological change, accelerated by digital transformation, is expected to positively influence the efficiency of European insurers. Second, efficiency and productivity dynamics are assumed to differ across life, non-life, and composite insurers due to their distinct business models and risk structures.

Accordingly, the paper empirically examines whether the observed efficiency improvements in the European insurance market are driven primarily by technological progress or by better management of inputs and outputs. In line with these objectives, the paper assesses how efficiency and productivity evolved in the EU insurance market between 2014 and 2023. The Data Envelopment Analysis (DEA) and the Malmquist index are applied to evaluate insurance efficiency. In line with the aim of the paper, we stated the following research questions: *Is the increase in efficiency of European insurance companies driven by technological change? Does efficiency and productivity (as measured by the Malmquist index) differ across insurance specializations (life, non-life, and composite)?* These questions allow us to link technological development with operational performance and to explore whether specialization shapes efficiency patterns in the European insurance industry.

The structure of the paper is as follows. The literature review in the second section highlights prior research and gaps addressed by this study. Section 3 presents the data and methodology; Section 4 discusses the results and efficiency trends across EU countries. The final section concludes with key findings, policy implications, and directions for future research.

2. Literature Review

2.1. Digitalization of the insurance industry

Digitalisation fundamentally transforms insurance markets, offering a variety of opportunities and challenges. Modern information technology (IT) solutions increase the efficiency of processes such as selling insurance policies, reporting insurance claims or financial reporting, leading to better customer service and significant operational streamlining (Novović-Burić and Stojanović 2022).

The authors Chojan et al. (2022) focused on efficiency and identified the importance of trends such as automation and point out that the automation of processes accelerates service delivery and reduces the number of manual errors, contributing to cost savings. The key benefits of digitalisation are accuracy, transparency, and timeliness in financial management. The possibilities of real-time data analysis and automated reporting support better planning and decision making in real time, as stated by Novović-Burić and Stojanović (2022). Digital platforms enable service personalization and strengthen customer relationships, while artificial intelligence enhances the user experience (Cappiello 2018; Chojan et al. 2022). Digital tools also increase the revenues of insurance intermediaries and support the growth of insurance contracts and the increase in written premiums (Köhne and Köhne 2024).

However, digitalisation brings risks. The main issues include IT outsourcing, system incompatibility, and growing concerns about data security, which can negatively impact customer trust (Chojan et al. 2022). Another risk lies in the potential loss of personal contact between insurance companies and clients, which could affect relationships and long-term loyalty, as noted by Cappiello (2018). Furthermore, digital stress is emerging among employees, which can hinder their performance if not properly managed (Köhne and Köhne 2024).

For full utilisation of the potential of digitalisation, strategic adaptation to market demands, proactive innovation, and effective problem solving are essential. Key priorities include a deep understanding of markets, technological development, product innovation, and the importance of cost management (Cappiello 2018).

Technological progress in insurance sector has led to increased efficiency through digital transformation, improving data collection and analysis, optimizing underwriting, and customer services (Ostagar 2018). The introduction of mobile and online platforms expanded the market, leading to higher gross written premiums (Nepochatenko et al. 2023; Grigorie and Tălăban 2024). Automation and advanced analytics optimized risk assessment and claim processing, improving the technical results of insurance accounts (Monkiewicz and Monkiewicz 2023). However, technology has also brought complex challenges, including regulatory issues and adverse effects in some cases, indicating the need for careful adaptation by insurers (Grigorie and Tălăban 2024; Nepochatenko et al. 2023). Research by Cappiello (2020) highlights that technological development, such as Big Data and digital communication methods, significantly impacts the insurance value chain, increasing customer engagement and operational efficiency. The ongoing process of digitalization is crucial for traditional insurers to adapt and remain competitive in the rapidly changing, technology-driven market. InsurTech solutions enable better risk management and customer engagement, leading to higher efficiency and profitability for insurers.

2.2. Measurement of insurance efficiency

The efficiency of the insurance companies was measured in several studies, especially the Data Envelopment Analysis method was used. Although, Kaffash and Marra (2017) showed that US, Taiwan and China have the largest number of papers on the application of DEA in the insurance industry in case of geographical distribution of insurance group. Several studies evaluate the efficiency of insurance companies in European Union countries. These studies were mostly focused on the period covered the global financial crisis. E.g. Cummins and Rubio-Misas (2022) using the Data Envelopment Analysis evaluated 10 EU life insurance markets over the period 1998–2014 and found the convergence in cost/revenue technology gap among these markets, suggesting that industries become more technologically homogeneous during the 1998-2014. However, the global financial crisis has led to a slowdown in the progress of integration and convergence in efficiency and technology gap of EU life insurance markets in terms of cost efficiency but not in terms of revenue efficiency. Eling and Schaper (2017) applied DEA on a sample of 970 life insurance companies from 14 European countries. The authors found no technical change in the European life insurance sector, and they nonetheless observe an efficiency increase in 2002–2013 that leads to an increase in total factor productivity; these trends can be explained by more challenging business conditions in the 2000s.

Eling and Luhnen (2009) measured the efficiency of 6462 insurers from 36 countries considering life and non-life insurers. The authors found a steady technical and cost efficiency growth in international insurance markets from 2002 to 2006, with large differences across countries. From the European countries, Denmark has the highest average efficiency. Kasman and Turgutlu (2011) analyzed the cost efficiency in the European insurance market over the period 1995–2005. They found that all insurance systems display significant levels of cost inefficiency and their analyses suggest similar results for major EU countries, new members and the candidate.

Kaffash et al. (2020) provided a review of 132 data envelopment analysis studies in the insurance industry and supposed that the Malmquist index has been widely adopted in studies. The Malmquist index has its advantages when estimating the changes in the total factor of productivity. Moreover, Bertoni and Croce (2011) applied DEA and Malmquist index to a panel of 602 life insurance companies in five countries (Germany, France, Italy, Spain and U.K.) between 1997 and 2004. The authors found that efficiency increased that was mostly due to innovation in best-practices. Their results indicated that innovation of best-practices was attributable to technological change and new technologies were more flexible. Nektarios and Barros (2010) applied the Malmquist index on the Greek insurance industry and found that the life sector experienced highest average annual productivity growth and the lowest growth was in the group of mixed insurance companies.

From the literature is visible that the studies about the insurance efficiency of the European Union countries in recent period are rare. Therefore, this paper can fill the existing knowledge gap.

3. Methodology and Data

The Data Envelopment Analysis is a widely used methodology to evaluate the performance/efficiency of different organizational systems. DEA is a nonparametric or mathematical programming technique used to evaluate the relative efficiencies of a set of decision-making units (Bruni et al. 2009). In this paper the decision-making units (DMUs) are commercial insurance companies. DEA measures the relative efficiency; the methodology consists in compares DMUs with a frontier of efficiency.

The DEA originated from the work of Charnes et al. (1978). The CCR (Charnes, Cooper and Rhodes) model assumes constant returns to scale (CRS) and evaluates overall technical efficiency without considering the scale of operations. This model posits that inputs and outputs increase proportionally. The CRS assumption is valid only when all DMUs function at optimal scales. However, in practice, DMUs may experience either economies or diseconomies of scale. Therefore, applying the CRS assumption incorrectly can distort technical efficiency measurements by incorporating scale efficiencies. Banker et al. (1984) advanced the CCR model by introducing variable returns to scale (VRS) with the BCC (Banker, Charnes and Cooper) model. The BCC model, which accounts for varying marginal benefits, is more appropriate for practical evaluations of insurance efficiency. Therefore, in this paper, the model with variable return to scale is used.

DEA initiates with a fractional programming framework. It is posited that there exist n DMUs for assessment. DMU$_j$ utilizes x_{ij} quantities of input to generate y_{rj} quantities of output. It is presumed that inputs, x_{ij}, and outputs, y_{rj}, are non-negative, with each DMU possessing at least one positive input and output. The efficiency of a DMU can be expressed as

$$h_j = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}}$$

In this equation, u and v denotes the weights for inputs and outputs. DEA employs mathematical programming techniques to optimally assigns the weights subject to the following constraints. The weights for each DMU are constrained to ensure no other DMU has efficiency greater than 1 if it uses the same weights, implying that efficient DMUs will have a ratio value of 1. The objective function of DMU is the ratio of the total weighted output divided by the total weighted input:

$$\max h0\,(u,\,v) = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}}$$

subject to
$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1,\; j = 1,2,\dots,j0,\dots,n,$$
$$u_r \geq 0, \qquad r = 1,2,\dots,s,$$
$$v_i \geq 0, \qquad i = 1,2,\dots,m,$$

where h_0 is the technical efficiency of DMU_0 to be estimated, u_r and v_i are weights to be optimized, y_{rj} is the observed amount of output of the r^{th} type for the j^{th} DMU, x_{ij} is the observed amount of input of the i^{th} type for the j^{th} DMU, r indicates the s different outputs, i denotes the m different inputs and j indicates the n different DMU_s.

Conditions of BCC model:

$$\max h_0 = \sum_{r=1}^{s} u_r y_{r0} + u_0,$$
$$\sum_{i=1}^{m} v_i x_{i0} = 1,$$
$$\sum_{r=1}^{s} u_r y_{r0} - \sum_{i=1}^{m} v_i x_{i0} + u_0 \leq 0,$$
$$v_i \geq 0,\, u_r \geq 0, \qquad j = 1,2,\dots,n, \qquad i = 1,2,\dots,m, \qquad r = 1,2,\dots,s,$$

where index $_0$ shows DMU, which efficiency is estimated, x_s denotes inputs, y_s denotes outputs, v_s is value of efficiency of the DMU, n shows number of DMU, m in number of inputs, s is number of outputs, u_0 denotes return to scale.

In classical DEA literature, the Malmquist index (MI) and window analysis are the unique methods of DEA that can analyse the change in efficiency over the time (Sanchez, 2018). Window DEA extends the traditional DEA model by evaluating the performance of DMUs over multiple time periods or windows. This method is useful for tracking changes in efficiency over time. In this paper, the Malmquist index will be used because it can be divided into two parts: efficiency change and technological change. The Malmquist index measures the relative efficiency change of a DMU in multiple time period and is an example in comparative statistics analysis (Cooper et al. 2007). The Malmquist index was introduced by Caves et al. (1982) and developed further by Färe et al. (1992) and Färe et al. (1994). The index is usually applied to the measurement of efficiency change over time and can be multiplicatively decomposed into an efficiency change index and a technological change index (Shahverdi and Ebrahimnejad 2014). One of the primary advantages of Malmquist index is that it would not involve the producer's behavior optimization assumptions, and these units can be deficient (Khosravi et al. 2015). When $MI > 1$ the DMU has improvement on productivity or efficiency and once $MI < 1$ the DMU experiences a decrease on efficiency (Khosravi et al. 2015).

Färe et al. (1994) use the DEA to construct an input-based MI between period t (the base period) and period s:

$$M_I(y^s, x^s, y^t, x^t) = \left[\frac{D_I^t(y^s, x^s)}{D_I^t(y^t, x^t)} * \frac{D_I^s(y^s, x^s)}{D_I^s(y^t, x^t)} \right]^{\frac{1}{2}},$$

where $M_I(\cdot)$ is the input-oriented MI, $D_I^t(y^s, x^s)$ is the distance function showing a maximal proportional reduction of the observed period s inputs under the period t technology. The distance function is defined as follows:

$$D_I^t(y^s, x^s) = \min_{\theta,\lambda} \theta,$$

subject to

$$y_{is} \leq \lambda Y^t,$$

$$\theta x_{is} \geq \lambda X^t,$$

$$\lambda_i \geq 0, i = 1, ..., n,$$

where θ is a scalar and λ is a vector of constants. The value of θ obtained is the component score of the i-th company. X and Y are input and output vectors, and the amounts of the i^{th} input consumed and output generated by the DMU_0, are denoted by x and y.

Assumption that $D_I^t(y^t, x^t)$ and $D_I^s(y^t, x^t)$ should equal to one, and allowing for technical inefficiency, Färe et al. (1992) decompose the Malmquist index into two components:

$$M_I = \left[\frac{D_I^t(y^s, x^s)}{D_I^t(y^t, x^t)} * \frac{D_I^s(y^s, x^s)}{D_I^s(y^t, x^t)} \right]^{\frac{1}{2}} = \frac{D_I^s(y^s, x^s)}{D_I^t(y^t, x^t)} \left[\frac{D_I^t(y^s, x^s)}{D_I^s(y^s, x^s)} * \frac{D_I^t(y^t, x^t)}{D_I^s(y^t, x^t)} \right]^{\frac{1}{2}}.$$

The first component $EC = \dfrac{D_I^s(y^s, x^s)}{D_I^t(y^t, x^t)}$ measures the change in technical efficiency (efficiency change, EC). The second component $TC = \left[\dfrac{D_I^t(y^s, x^s)}{D_I^s(y^s, x^s)} * \dfrac{D_I^t(y^t, x^t)}{D_I^s(y^t, x^t)} \right]^{\frac{1}{2}}$ measures the technology frontier shift (technological change, TC) between time period t and s. Färe et al. (1992, 1994) point out that a value of $TC > 1$ indicates a positive shift or technical progress, a value of $TC < 1$ indicates a negative shift or technical regress, and value of $TC = 1$ indicates no shift in technology frontier.

The data set utilized in this paper was obtained from the Moody's Analytics Orbis during the period 2014-2023. We consider insurance companies across 27 European Union member countries. All the data is reported on an unconsolidated basis. An unbalanced panel data was used with the sample of 1823 commercial insurance companies. Because DEA measures relative efficiency with respect to other entities in the sample, we distinguish between life, non-life and composite insurance companies. We covered the sample of 375 composite insurance companies, 464 life and 984 non-life insurance companies in 27 European Union countries during the period 2014-2023. All monetary variables were downloaded in euros, any currency conversion is performed within the Orbis database.

The data set included 27 European Union countries: Austria (AT), Belgium (BE), Bulgaria (BG), Croatia (HR), Cyprus (CY), Czech Republic (CZ), Denmark (DK), Estonia (EE), Finland (FI), France (FR), Germany (DE), Greece (GR), Hungary (HU), Ireland (IE), Italy (IT), Latvia (LV), Lithuania (LT), Luxembourg (LU), Malta (MT), Netherlands (NL), Poland (PL), Portugal (PT), Romania (RO), Slovakia (SK), Slovenia (SI), Spain (ES), Sweden (SE).

To conduct DEA-Malmquist analysis, the specification of inputs and outputs is essential. We used three inputs: total investment (TI), total underwriting expenses (TUE) and total gross insurance provisions (TGIP) and three outputs: gross premiums written (GPW), earned premiums (EP) and balance on combined technical account (BCTA). The input–output set follows common practice in DEA studies of insurers. Underwriting expenses and technical provisions are standard inputs reflecting operating effort and risk-bearing capacity, while investments proxy the financial capital deployed. On the output side, written and earned premiums capture production and realized insurance services; the combined technical account summarizes underwriting performance. Similar configurations are used across European samples and life/non-life settings (e.g., Eling and Schaper, 2017; Bertoni and Croce, 2011; Nektarios and Barros, 2010 or Kaffash et al., 2020).

The total investment indicates the foundational capital of the insurance company, highlighting financial management's impact on insurer efficiency. It also signifies the capital dedicated to traditional and digital operations that improve efficiency and customer satisfaction. Total underwriting expenses represent the costs linked to evaluating, pricing, and issuing insurance policies, playing a critical role in assessing operational efficiency and profitability. Effective management of these expenses is vital for maintaining competitive advantage, while digitalization can enhance underwriting efficiency and reduce costs. Gross insurance provisions, encompassing reserves for future claims, are essential inputs within the insurance sector. They signify the anticipated liabilities of the insurer, and their efficient management is key to ensuring solvency and financial stability.

Gross premiums written denote the total revenue accrued from sold insurance policies within a defined timeframe, reflecting the insurer's market appeal and demand for its offerings, which are vital for operational success. Earned premiums correspond to the premiums related to the insurance coverage provided during the period, serving as a direct indicator of the insurer's income generation relative to its risk exposure. The balance on the combined technical account illustrates the overall underwriting outcome after accounting for claims, reinsurance, and operational costs. This metric serves as a holistic assessment of the insurer's efficiency and profitability in managing underwriting and claims.

Table 1 Descriptive Statistics of input and output variables

	TI	TUE	TGIP	GPW	EP	BCTA
Mean	8142139	1113827	7356370	966851.8	975780.5	56403.69
Median	299159.9	68426.22	254237	78390	65222	2551
St.Dev.	42987761	5305604	38811823	4410806	4530230	1041280
Min	0.00001	-7.1E+07	-16395	-78171	-1780491	-2.9E+07
Max	9.73E+08	1.15E+08	9.05E+08	99852000	91337000	87128000

Source: Authors' calculations.

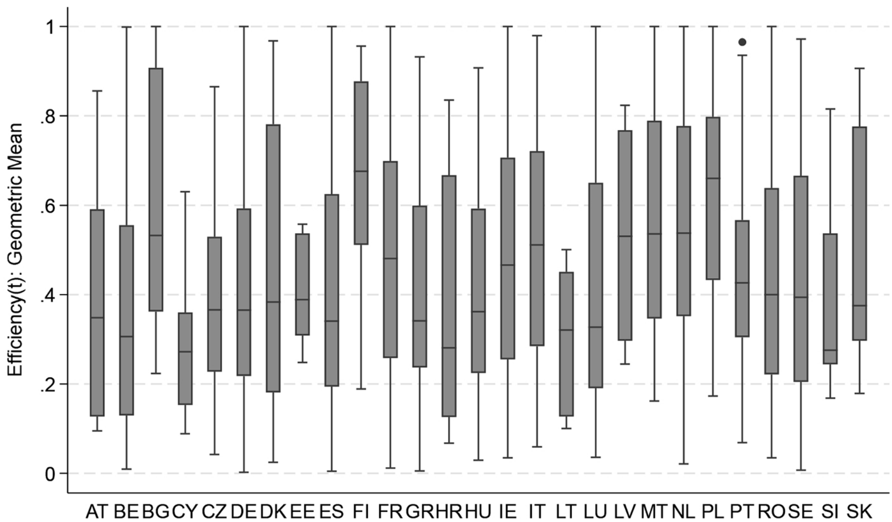
4. Research Results and Discussion

The empirical analysis of this study focuses on evaluating the efficiency of insurance companies in the European Union using Data Envelopment Analysis and the Malmquist index. We used the slack-based (non-oriented) measured model with variable return to scale.

Because DEA frontiers are sensitive to extremes, we used the super-efficiency analysis. An efficient DMU with a very high super-efficiency score is likely an outlier and we removed these outlier observations from our results.

In Figure 1 the results showed that there are significant differences in insurance efficiency between individual countries in 27 European Union countries. The EIOPA report (2024b) highlights significant differences in the level of technological development between EU countries in the insurance sector. Digitalization is still in its early stages, and progress varies by country. The adoption of new technologies such as artificial intelligence, blockchain, and the Internet of Things presents new opportunities for insurers, distributors, and consumers. The European Commission supports the digitalization of financial services and, in 2020, adopted the Digital Finance Package, which includes initiatives like the Data Act and the Digital Markets Act. EIOPA focuses on promoting the digital transformation of insurance and responds flexibly to rapid technological advances to minimize risks and harness the opportunities associated with digitalization. Moreover, Bayar et al. (2023) supported that internet penetration has a significant positive influence on insurance sector growth in 10 EU new EU member countries. This result can support the significant digitalization in insurance industry, in addition countries with higher ICT penetration tend to perform better in insurance development.

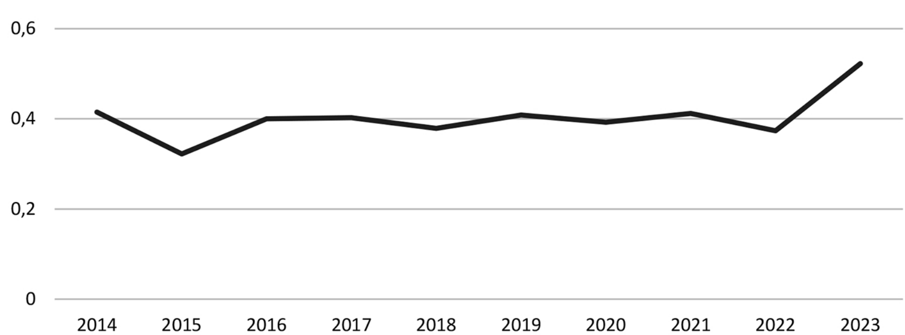
Figure 1. Box plot of insurance efficiency during the period 2014-2023 in EU countries



Source: Authors' calculations.

Technological advances in European insurance industry between 2014 and 2023 have led to slight improvements in efficiency, stability, and consumer protection. During the observed period, differences in efficiency development can be observed, which are related to technological progress (see Figure 2). The development of the insurance efficiency was almost stable during the analysed period, slight decrease was visible in year 2015 and 2021, but during the period 2022-2023 is visible increase in efficiency.

Figure 2. Insurance efficiency development in European Union during the period 2014-2023



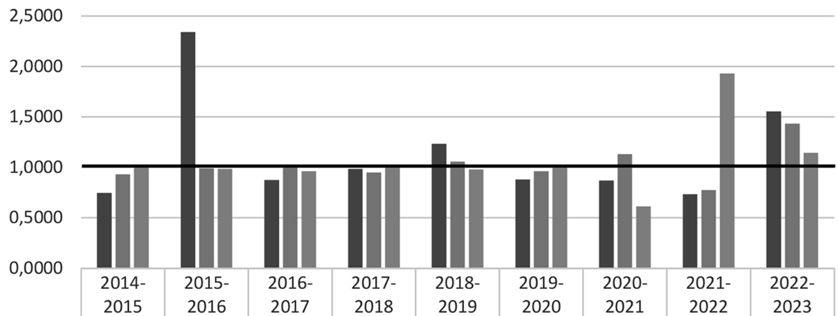
Source: Authors' calculations.

The 2014-2015 period, despite the absence of major technological breakthroughs, was crucial to the preparation of Solvency II. As noted by EIOPA (2024a), it involved the modernization of data infrastructures, the introduction of advanced risk management mechanisms and analytical tools. These preparatory steps improved transparency and efficiency, and their full impact became evident after 2016. In some countries, early experiments with cloud technologies emerged, laying the foundation for greater flexibility, more efficient data management, and cost reduction (Czech Statistical Office, 2024). Since 2010, the development of client service digitalization and the implementation of self-service portals have been observable. Digital technologies have begun to be used in all stages of insurance products, including design, distribution, and policy administration.

The EIOPA Annual Report (2016) highlights that the Solvency II regime, implemented in 2016, brought technological innovations and improved the efficiency of insurers. EIOPA provides significant assessments regarding the introduction of Solvency II in 2016. The implementation of Solvency II modernized capital requirements and risk management, supported digitalization, leveraged big data, and improved data transparency and quality. The regulatory framework allowed for better supervision, more efficient risk management, and operational processes. A major milestone was the acquisition of the first complete reporting data, which promoted innovation and adaptability of insurers to new challenges. EIOPA (2021b) launched its digital transformation in 2018, focusing on technological innovations in insurance supervision, known as SupTech. These initiatives led to process automation, more efficient use of data, and strengthened supervision mechanisms.

Since 2021, the graph shows a significant increase in efficiency within European insurance industry (Figure 3). It is evident that the COVID-19 pandemic (EIOPA, 2020) accelerated insurance digitalization, including online product distribution and digitalization of client services. EIOPA had to respond to this development with a series of gradual steps in the following years. It was necessary to address the advancement of technologies and the growing technological/cyber risks. In 2021, (2021a) introduced its digital strategy, which included the development of a data ecosystem, support for artificial intelligence, ensuring financial stability, a unified market, and enhanced supervisory capabilities. In the same year, the SupTech strategy was published, emphasizing the use of technology to improve supervision and enable the early identification of risks. In 2022, the Digital Operational Resilience Act (DORA 2022) was adopted, establishing a unified framework for financial institutions' resilience to cyber threats. Strengthening IT infrastructures, improving cybersecurity, and improving insurer operational resilience. Regular financial stability reports from the European Central Bank and EIOPA (2014-2023) highlighted the crucial role of technological innovations in the stability of the financial sector and provided valuable input for policy making. These measures improved the ability to meet customer needs and increased operational efficiency. In 2023, EIOPA (2023) updated its digital strategy for the 2024-2026 period, promoting transformation in consumer services, markets, and supervision.

Figure 3. Efficiency change of insurers in European Union



	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019	2019-2020	2020-2021	2021-2022	2022-2023
Life	0,7480	2,3403	0,8738	0,9849	1,2343	0,8799	0,8694	0,7349	1,5533
Non-life	0,9303	0,9892	1,0064	0,9487	1,0563	0,9621	1,1323	0,7741	1,4344
Composite	1,0163	0,9859	0,9619	1,0139	0,9803	1,0174	0,6147	1,9309	1,1450

Source: Authors' calculations.

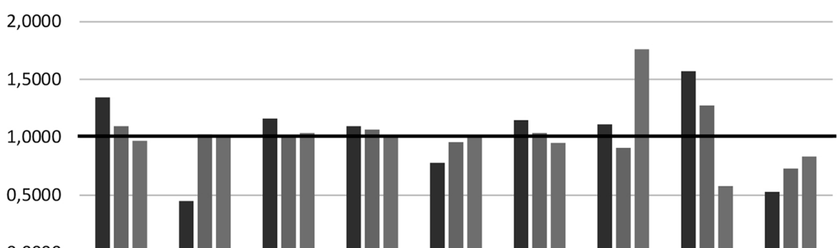
We calculated the average Malmquist index and its decompositions of the commercial insurance companies in 27 EU countries during the period 2014-2023, We measured the efficiency for life insurers, non-life insurers and composite insurers.

The Malmquist index (Figure 5) is higher than one during whole analysed period in non-life insurance companies. It indicates that non-life insurers in EU countries increased productivity and efficiency in these periods. In case of composite insurers, the Malmquist index is higher than one in most of periods (except the 2015-2016 and 2019-2020). The life insurance companies did not reach the value higher than one in most of periods. Over 2014–2023, the non-life segment shows a Malmquist index above 1 on average, it indicates the productivity growth, whereas the life segment records Malmquist index lower than 1 in most period. At the same time, life insurers display higher technical efficiency levels than non-life, which may be reflected in lower Malmquist index values. The Malmquist index equals catch-up (efficiency change) times frontier shift (technical change). Higher technical efficiency score in life means life insurers are close to the frontier within each year. Malmquist lower that 1 indicates that the frontier itself moved inward for life (technical change < 1) or that catch-up did not offset that inward shift. In non-life, positive technical change and/or faster catch-up pushed Malmquist higher than 1. The ability to balance efficiency and technological change remains a key success factor, with investment in innovation and process improvement playing a critical role.

If we consider the possible economic consequences in the given period, then during the period 2014–2019 it could be probably caused by fact that prolonged low rates and legacy guarantees in life increased reserving and capital intensity (it means larger inputs), depressing technical change; non-life benefited from pricing/claims digitalization and cost control (frontier shift outward). During the COVID-19 period 2020-2021 it could lead to the temporary declines in claim frequencies in key non-life lines (e.g., motor, travel) improved productivity; life faced disruptions in distribution and investment re-pricing, keeping total factor productivity subdued. Moreover, higher inflation and rates during 2022-2023 could probably support new business economics in life but revaluation of liabilities/portfolios and distribution costs kept technical change muted. Non-life absorbed inflation via repricing and operational gains, sustaining positive frontier movement.

When we consider the efficiency change (Figure 3) and technological change (Figure 4), we found that the efficiency increased due to the better management of inputs and outputs and efficiency improvements during the years 2018-2019 and 2022-2023. In the years 2017-2018 and 2019-2022, the strong technological progress was the main factor of efficiency increasing. During the period 2018-2019 the decline in MI (especially life insurance) indicate a period of stagnation, where technological change declined and efficiency. The increased in 2020-2021 could be caused likely due to adaptation to pandemic challenges and the introduction of technological innovation. However, decrease in MI in 2022-2023 may indicate an inability to sustain previous improvements in efficiency and technological progress.

Figure 4. Technological change of insurers in European Union

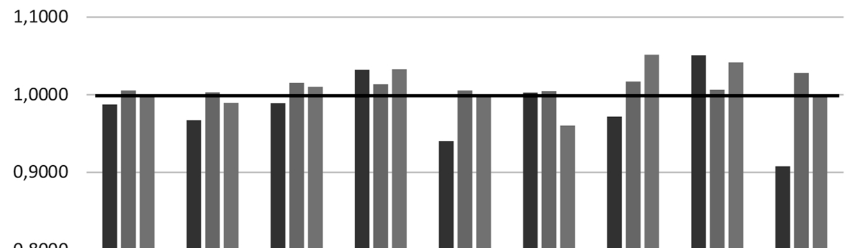


	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019	2019-2020	2020-2021	2021-2022	2022-2023
Life	1,3441	0,4494	1,1620	1,0961	0,7785	1,1473	1,1112	1,5708	0,5273
Non-life	1,0953	1,0233	1,0031	1,0671	0,9570	1,0368	0,9090	1,2748	0,7294
Composite	0,9702	1,0017	1,0367	1,0193	1,0147	0,9508	1,7610	0,5788	0,8348

Source: Authors' calculations.

The development of EC and TC differs during individual periods. Over 2014–2023, non-life insurers show slight efficiency (MI) growth (geometric mean MI = 1.0075), whereas life insurers are broadly flat to slightly negative (MI = 0.9938). The gap is driven mainly by technical change, the non-life frontier shifts outward on average (TC = 1.016), while the life frontier contracts in several key sub-periods (TC ≈ 0.997). Within-year efficiency (catch-up) is broadly similar across segments (EC around 1).

Figure 5. Malmquist index of insurers in European Union



	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019	2019-2020	2020-2021	2021-2022	2022-2023
Life	0,9875	0,9671	0,9893	1,0321	0,9403	1,0027	0,9717	1,0508	0,9079
Non-life	1,0053	1,0029	1,0153	1,0134	1,0053	1,0048	1,0168	1,0063	1,0279
Composite	1,0000	0,9894	1,0100	1,0328	1,0000	0,9605	1,0515	1,0417	1,0000

Source: Authors' calculations.

In 2015-2016 in case of life insurance there is significant increase in efficiency change but decrease in technological change, that influence also final Malmquist index. It can show that companies are rapidly catching up, while the frontier is reducing. Change during 2019-2020 and 2021-2022 the technological change in life and non-life insurance increased.

In case of life insurance, the higher level of technical efficiency, but MI often below 1, as the frontier shifted inward in several key years (TC < 1 during the years 2015-2016, 2018-2019, 2022-2023). This is consistent with pressures from guarantees, re-pricing of liabilities, and capital/interest intensity when rates change. In case of non-life insurance, we can see more stable TC ≥ 1 overall and episodes of strong efficiency change (2020-2021, 2022-2023), giving MI slightly above 1. In line with faster repricing capabilities, digitization of claims, and cost management. In composite insurance segment there is visible the mix of effects. We see technological change shocks (1.761 in 2020-2021; 0.579 in 2021-2022) and EC fluctuations. Geometric mean of Malmquist index around 1.005 shows slight growth in efficiency.

Table 2 presents the average efficiency and Malmquist index in individual insurance markets. We can see the differences between individual countries. The Malmquist index is higher than one in the most of insurance market. Therefore, in most countries, the overall productivity and efficiency of insurance companies was increasing during analysed period. This growth is the result of a combination of technological progress and changes in efficiency. However, the Malmquist index was less than 1 in Austria, Bulgaria, Germany, Denmark, Ireland, Latvia and Portugal, indicating a decrease in overall productivity/efficiency. This result may be due to either weak technological progress (Bulgaria, Denmark and Ireland), insufficient efficiency improvements (Portugal) or a combination of both factors (in case of Latvia).

The technological change is greater than 1 in only 10 countries (Austria, Finland, France, Greece, Croatia, Italy, Lithuania, Poland, Portugal and Sweden), indicating that there were technological advances in these countries that contributed to increased productivity/efficiency. These countries are likely to have invested in innovation, digitisation and process modernisation. In the other countries, technological progress has slowed down or stagnated. This may indicate limited investment in new technologies or inefficient implementation. Weak technological progress, therefore, means that insurers do not adopt or use new technologies. Therefore, low technological change in several countries suggests that efficiency depends more on efficiency, better management of inputs and outputs than on technological innovation.

Table 2. The average efficiency, Malmquist index, Technological change and efficiency change during the period 2014-2023

Country	Efficiency	Efficiency Change	Technological Change	Malmquist Index
AT	0.4035	0.9614	1.0386	0.9923
BE	0.3700	1.0631	0.9782	1.0060
BG	0.5972	1.0858	0.8591	0.9300
CY	0.2978	1.1511	0.9658	1.0509
CZ	0.3838	1.1376	0.9643	1.0508
DE	0.4143	1.0674	0.9680	0.9932
DK	0.4615	1.0661	0.9744	0.9988
EE	0.3986	1.1456	0.9440	1.0157
ES	0.4150	1.1018	0.9543	1.0036
FI	0.6611	1.0071	1.0174	1.0234
FR	0.4901	1.0039	1.0195	1.0104
GR	0.4027	1.0365	1.0448	1.0291
HR	0.3589	1.0834	1.0039	1.0725
HU	0.3942	1.1461	0.9112	1.0013
IE	0.4958	1.0448	0.9863	0.9885
IT	0.5101	1.0041	1.0098	1.0050
LT	0.3131	0.9989	1.0128	1.0073
LU	0.4085	1.1612	0.9363	1.0177
LV	0.5323	0.9784	0.9715	0.9441
MT	0.5662	1.0148	0.9973	1.0120
NL	0.5505	1.0640	0.9906	1.0185

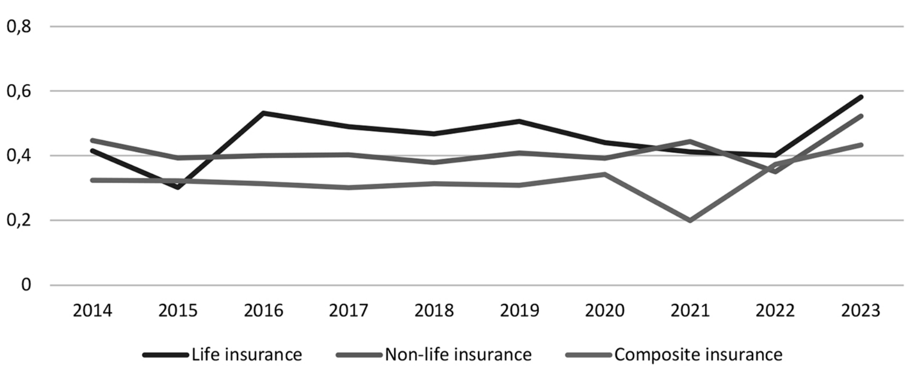
PL	0.6151	1.0065	1.0127	1.0187
PT	0.4498	0.9820	1.0220	0.9979
RO	0.4302	1.0981	0.9688	1.0324
SE	0.4361	1.0365	1.0202	1.0520
SI	0.3864	1.0511	0.9803	1.0289
SK	0.4969	1.0584	0.9944	1.0540

Source: Authors' calculations.

In summarize, the results show that overall productivity is positive in most countries, which means that insurance companies in these countries indicate growth in efficiency. However, the low technological change values in most countries suggest that growth is more dependent on efficiency improvements than on technological innovation. Moreover, DEA measures relative performance against the best observed peers in the sample. Countries with many small, specialized insurers can span the frontier, whereas large, diversified German insurers carry higher technical provisions, compliance and distribution costs, and more complex product mixes that increase measured inputs. Accordingly, for example, lower German efficiency does not imply inferior management, but rather reflects a different scale and business mix under a pooled technology.

Figure 6 showed that the life insurers were the highest efficient during the period 2016-2020 and 2022-2023, but the efficiency of life insurers slightly decreased in 2020-2022. On the other hand, the composite insurers were less efficient than the life and non-life insurers and the efficiency slightly decreased in 2021. The efficiency of non-life insurers was stable during the analysed period with slight increase in 2021 and 2023. significantly increased in 2023. We measured the efficiency of insurance companies using Malmquist index and its decomposition into efficiency and technology change.

Figure 6. Efficiency of insurance companies in EU according to the specialization



Source: Authors' calculations.

Our finding confirmed the previous studies, e.g. Witkowska (2023) concluded that the slight decline in efficiency from 2021 to 2023 could be attributed to challenges in adapting to digital transformation and maintaining cost efficiency amidst evolving consumer expectations. Moreover, non-life insurers saw a significant increase in efficiency in 2023, likely driven by technological innovations and improved risk management practices (Kumar and Kumar 2024). The ability to quickly adapt to market changes and leverage data analytics for better underwriting and claims processing has contributed to their enhanced performance (Witkowska 2023).

5. Conclusions

The paper analysed the efficiency of the commercial insurance companies in 27 European Union countries during the period 2014-2023. We applied the Data Envelopment Analysis and Malmquist index and its decomposition for empirical analysis.

The results show the significant differences in insurance efficiency across the 27 countries of the European Union. The Malmquist index highlights fluctuations in productivity within the EU insurance sector, with increases in 2016-2018 and 2021-2022, indicating successful adaptation and innovation. Conversely, there were decreases in periods such as 2018-2019 and 2022-2023 (especially in life insurance), pointing to challenges such as stagnating efficiency and slowing technological progress. Investment in innovation and process improvements plays a key role. Overall, the results show positive productivity trends in most countries, indicating that insurance companies are becoming more efficient. However, the low values of technological change in many countries suggest that this growth is more dependent on efficiency improvements than on technological innovation.

Considering the specialisation of insurance companies, life insurers were the most efficient, although their efficiency decreased slightly between 2021 and 2022. In contrast, non-life insurers experienced a slight increase in efficiency in 2021 and 2023. For insurance companies, technological change was the main driver of efficiency improvements in most of the analysed period. While better management of inputs and outputs was the main driver in 2022-2023, with technological change playing a less important role.

When we consider our research questions: *Is the increase in efficiency of European insurance companies driven by technological change?* The increase in efficiency of European insurance companies is not primarily driven by technological change. The finding indicates that while there are periods of significant technological advancements, the overall growth in efficiency is more dependent on improvements in efficiency rather than technological innovation.

Does efficiency and productivity (as measured by the Malmquist index) differ across insurance specializations (life, non-life, and composite)? There is a difference in efficiency and the Malmquist index based on the insurers' specialization. Life insurers were found to be the most efficient, although their efficiency significantly declined during 2021-2022. Moreover, technological change was more significant for non-life insurers, while efficiency improvements in life and composite insurance companies were mainly due to better management of inputs and outputs.

There are several limitations of this research. We consider the life, non-life and composite insurance companies. We used the static DEA model and Malmquist index to allow us to use an unbalanced panel and not have to remove insurers that did not work throughout the analysis period. But dynamic methods can better capture changes in efficiency. We can deeply focus on the specific inputs and outputs of the individual specialization of insurers. Moreover, since we have estimated the relative efficiency of commercial insurers in the context of other insurance companies within the sample, it is crucial to interpret the results cautiously and in light of the specific context in which they were analysed. Significant differences exist in the structure of EU economies, including factors such as the size of the economy, the productive orientation of various industries, and the overall economic environment. These structural disparities may influence the efficiency of insurance companies and should be carefully considered when drawing conclusions from the results.

The research pointed that it is very important topic and in the empirical literature is gap in this issue. Moreover, in the future research it is necessary to focus on the determinants of the insurance efficiency. We will use the two-stage DEA model, namely Bootstrap analysis to analyse the influence of the macroeconomic and insurance specific factors.

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Dynamic Relationship Between External Economic Shocks and Banking Stability: Empirical Evidence from Indonesia Banking Sector

Relação Dinâmica Entre Choques Económicos Externos e Estabilidade Bancária: Evidência Empírica do Sector Bancário Indonésio

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ABSTRACT

Banking stability is critical for financial resilience in open emerging economies exposed to external shocks. This study examines how external factors, the US Dollar Index, foreign exchange reserves, and foreign bank asset penetration, affect banking stability in Indonesia, proxied by the Loan-to-Deposit Ratio (LDR). Using monthly data from January 2020 to December 2024, the analysis applies a Vector Error Correction Model (VECM) complemented by Impulse Response Functions, Variance Decomposition, and Granger causality tests. The results reveal a significant long-run relationship between external variables and banking stability. US dollar appreciation and higher foreign bank penetration tend to weaken banking intermediation, while foreign exchange reserves enhance stability. In the short run, the banking sector remains vulnerable to external shocks, particularly from global dollar movements and foreign bank dominance. IRF and variance decomposition results confirm the growing contribution of external shocks to LDR fluctuations over time. Granger causality indicates that foreign exchange reserves and foreign bank penetration are key determinants

of banking stability. These findings underscore the importance of dynamic reserve management, exchange rate flexibility, and prudent macro prudential regulation to strengthen Indonesia's financial resilience amid global volatility.
Keywords: Banking Stability, Loan to Deposit Ratio (LDR), US Dollar Index, Foreign Exchange Reserves, Foreign Banks.

JEL classification: F41; F65; G21

1. Introduction

Global economic developments over the past decades have been characterized by heightened volatility in international financial markets, shifts in monetary policy stances in advanced economies, and increasing financial integration across countries. One key indicator reflecting these global dynamics is the US Dollar Index, which measures the relative strength of the United States dollar against a basket of major international currencies. Movements in the US Dollar Index play a central role in shaping global liquidity conditions, capital flows, and financial stability in emerging economies (Obstfeld, et al. 2019 ; Huang and Liao, 2023). A strengthening US dollar typically increases external financing costs, intensifies capital outflows, and tightens domestic liquidity conditions, thereby affecting banking sector stability in developing countries.

Indonesia represents a particularly relevant case for examining these global transmission mechanisms. As one of the largest emerging economies with a bank-dominated financial system, Indonesia combines moderate financial openness, substantial exposure to global capital flows, and a non-negligible presence of foreign banks in its domestic banking sector. Unlike advanced economies with deep and diversified capital markets, Indonesia relies heavily on banks as the primary channel of financial intermediation. Consequently, shocks originating from global financial conditions are more likely to propagate through the banking system and directly affect credit provision and liquidity management. This structural characteristic makes the Indonesian case especially informative for the broader literature on banking stability in emerging market economies.

For Indonesia, foreign exchange reserves serve as a key buffer against external volatility. Changes in foreign exchange reserves reflect not only macroeconomic fundamentals but also the dynamics of capital inflows and outflows. Adequate reserve buffers are widely regarded as an important policy instrument to mitigate external shocks and stabilize domestic financial systems during periods of global stress (Mishra and Sharma, 2021).

Furthermore, the role of foreign banks in the Indonesian banking system is also an important variable to consider. The ratio of foreign bank assets to total domestic banking assets indicates the degree of foreign financial institution involvement in domestic financial intermediation. While foreign banks may enhance efficiency and access to finance, they may also transmit external shocks into the domestic financial system (Claessens and Horen, 2015; Hasan, et al. 2022).

Banking stability in Indonesia is closely related to the performance of the intermediation function, commonly measured by the Loan-to-Deposit Ratio (LDR). During the 2020–2024 period, the Indonesian banking sector experienced substantial fluctuations in LDR. At the onset of the COVID-19 pandemic, the LDR declined sharply from 93.36% in January 2020 to 77.13% in December 2021, reflecting weakened credit demand, heightened uncertainty, and increased liquidity preference. As global and domestic conditions improved, the LDR gradually recovered, reaching 90.34% by December 2024. These developments indicate that banking intermediation in Indonesia is highly sensitive to external economic pressures and global financial cycles, rather than being driven solely by domestic banking fundamentals.

Although a growing body of literature has examined the influence of external factors on financial stability in emerging economies (Kim and Lee, 2020; Sharma and Shukla, 2022), empirical studies specifically linking the US Dollar Index, foreign exchange reserves, and foreign bank asset penetration to banking stability in Indonesia remain limited. Most existing studies on Indonesian banking stability focus primarily on domestic bank-specific indicators such as capital adequacy, asset quality, efficiency, and liquidity, while overlooking the role of global external variables. Moreover, much of the global literature relies on cross-country panel data, which may obscure country-specific transmission mechanisms and institutional features. As a result, there is limited empirical evidence documenting how global external shocks affect banking stability through the intermediation channel in Indonesia.

In addition, there is limited evidence regarding how the long-term relationship (cointegration) and short-term dynamics between external variables and banking stability in Indonesia operate. In fact, the 2020–2024 period showed LDR fluctuations that were in line with the dynamics of the three external variables, emphasizing the need for a more comprehensive analysis.

This study addresses these gaps by employing a Vector Error Correction Model (VECM) using monthly data from 2020 to 2024. The empirical results confirm the existence of a long-run equilibrium relationship between external economic factors and banking stability. In the long run, a strengthening US dollar and an increase in foreign bank asset penetration are associated with weaker banking intermediation, while foreign exchange reserves exert a stabilizing effect. In the short run, shocks to external variables generate persistent effects on the Loan to Deposit Ratio, underscoring the vulnerability of banking stability to global financial disturbances.

Beyond its relevance for Indonesia, this study contributes to the global literature by offering insights applicable to other emerging economies with bank-centered financial systems, exposure to global dollar cycles, and growing foreign bank participation. While institutional settings and degrees of financial openness differ across countries, the transmission mechanisms identified in this study are likely to be relevant for a broad set of emerging markets.

In addition, there is limited evidence regarding how the long-term relationship and short-term dynamics between external variables and banking stability in Indonesia operate. In fact, the 2020–2024 period showed LDR fluctuations that were in line with the dynamics of the three external variables, emphasizing the need for a more comprehensive analysis.

Thus, this study can provide important contributions by: (1) presenting the latest empirical evidence regarding the influence of external factors on the stability of banking intermediation in Indonesia, (2) applying the Vector Error Correction Model (VECM) to separate long-term and short-term effects and examine shock responses, and (3) offering policy implications for monetary authorities and banking regulators in anticipating external risks to banking stability.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 provides an overview of the Indonesian banking sector. Section 4 describes the data and methodology. Section 5 presents the empirical results, robustness checks and discussion. Section 6 concludes and shows the policy implications.

2. Literature Review

Banking stability in developing countries is increasingly shaped by global financial dynamics, particularly fluctuations in the global dollar cycle. The US Dollar Index serves as a widely recognized proxy for global liquidity conditions and reflects shifts in international capital flows and monetary policy spillovers from advanced economies. A strengthening US dollar is commonly associated with tighter global financial conditions, rising foreign currency funding costs, increased exchange rate volatility, and deteriorating investor sentiment (Obstfeld et al. 2019; Huang and Liao, 2023). These developments may directly affect domestic banking systems in emerging markets, especially those characterized by partial financial openness and exposure to external debt.

From an intermediation perspective, movements in the US Dollar Index may influence the Loan-to-Deposit Ratio (LDR) through multiple channels. On the one hand, tighter global conditions may induce banks to strengthen liquidity management and improve risk pricing. On the other hand, dollar appreciation often leads to domestic currency depreciation and capital outflows, which may constrain credit growth relative to deposit expansion. Emerging market banking systems, therefore, may experience credit contraction during episodes of global dollar tightening (Kim and Lee, 2020; IMF, 2024).

Foreign exchange reserves are widely viewed as a key macroeconomic buffer against external volatility. Theoretical and empirical studies suggest that adequate reserves enhance policy credibility, stabilize exchange rates, and provide foreign currency liquidity during periods of stress (Mishra and Sharma, 2021). Through these channels, foreign exchange reserves may support banking intermediation stability by reducing uncertainty and mitigating liquidity risks. However, maintaining large reserves entails sterilization and opportunity costs (ECB, 2019), and excessive reliance on reserves without complementary macroprudential instruments may create moral hazard. The effectiveness of reserves in stabilizing banking systems therefore depends on institutional quality and policy coordination (BIS, 2024; IMF, 2024).

In addition to global liquidity conditions and reserve buffers, the presence of foreign banks plays an important role in shaping domestic banking stability. The literature highlights both stabilizing and destabilizing effects. On the positive side, foreign banks may enhance efficiency, introduce advanced risk management practices, and diversify funding sources (Claessens and van Horen, 2015). Increased competition and technological spillovers can strengthen financial intermediation capacity. On the negative side, foreign banks may transmit external shocks through cross-border liquidity reallocation, particularly during episodes of global stress (Hasan et al. 2022). Parent banks may repatriate funds to headquarters, leading to credit contraction in host countries. Furthermore, selective lending behavior may reduce credit access for smaller or riskier borrowers (Sanya and Wolfe, 2018).

Recent cross-country evidence suggests that the impact of foreign bank penetration is heterogeneous and depends on regulatory quality, market structure, and supervisory coordination. Consequently, the interaction between global dollar dynamics, reserve adequacy, and foreign bank presence forms a complex framework through which external shocks may influence banking intermediation stability in emerging economies.

3. Overview of the Indonesia Banking Sector

To properly interpret the empirical findings, it is essential to understand the structural and statistical characteristics of the Indonesian banking system during the period of analysis (2020-2024). Indonesia operates a bank-dominated financial system in which commercial banks constitute the primary channel of financial intermediation. Credit provision to households and firms relies predominantly on banking institutions rather than capital markets, making banking stability central to macroeconomic stability.

During the 2020–2024 period, the Indonesian banking sector demonstrated resilience despite significant external shocks, including the COVID-19 pandemic and global financial volatility. Table 1 presents key banking indicators over the study period.

Table 1. Key Banking Sector Indicators in Indonesia (2020-2024)

Indicator	2020	2021	2022	2023	2024
Loan to Deposit Ratio (LDR)	82.54%	77.49%	78.98%	84.11%	88.57%
Capital Adequacy Ratio (CAR)	23.89%	25.66%	25.62%	27.75%	26.69%
Gross Non-Performing Loans (NPL)	3.06%	3.00%	2.44%	2.19%	2.08%
Deposit Growth (YoY)	11.11%	12.21%	9.01%	3.73%	4.48%
Loan Growth (YoY)	2.41%	5.24%	11.35%	10.38%	10.39%

Source: Otoritas Jasa Keuangan (OJK), Indonesian Banking Statistics (various issues).

As shown in Table 1, the Loan-to-Deposit Ratio (LDR) declined significantly during the pandemic, falling from 82.54% in 2020 to 77.49% in 2021, reflecting weakened credit demand and heightened liquidity preference. However, LDR gradually recovered in the post-pandemic period, reaching 88.57% in 2024, indicating a strengthening intermediation function.

In terms of capitalization, the Capital Adequacy Ratio (CAR) remained consistently well above the regulatory minimum threshold of 8%, increasing from 23.89% in 2020 to 26.69% in 2024. This indicates that Indonesian banks maintained substantial capital buffers during both crisis and recovery phases. Meanwhile, credit quality improved steadily, with gross NPL ratios declining from 3.06% in 2020 to 2.08% in 2024, suggesting effective risk management and loan restructuring policies during the pandemic recovery period.

From a liquidity and growth perspective, deposit growth was strong during the pandemic (above 11% in 2020-2021) due to precautionary savings and accommodative monetary policy. However, deposit growth moderated in 2023-2024 as economic activity normalized. Conversely, credit growth accelerated significantly in the recovery phase, exceeding 10% in both 2023 and 2024, contributing to the rising LDR.

Structurally, the Indonesian banking system consists of state-owned banks, private domestic banks, regional development banks and foreign banks. Market concentration remains relatively high, with large commercial banks dominating asset ownership. Regulatory oversight is conducted under an integrated financial supervisory framework with macroprudential instruments including capital requirements, liquidity coverage ratios and foreign exchange liquidity regulations designed to mitigate systemic risk.

Overall the statistical evidence suggests that the Indonesian banking system entered the post-pandemic period with strong capital buffers, improving asset quality, and recovering intermediation activity. However, the fluctuations in LDR and credit dynamics during 2020–2024 indicate sensitivity to both domestic and external macro-financial conditions. These structural and cyclical characteristics justify examining how external variables, such as the US Dollar Index, foreign exchange reserves and foreign bank penetration interact with banking intermediation stability in Indonesia.

4. Methodology and Data

This study uses a quantitative approach with econometric analysis based on the Vector Error Correction Model (VECM). VECM was chosen because it is able to analyze the dynamic relationship between cointegrated non-stationary variables, so that it can differentiate between long-run equilibrium and short-run dynamics (Johansen, 1988).

4.1. Data and data sources

This study used monthly time series data for the period January 2020 - December 2024. The variables used are in Table 2.

Table 2. Variable Definitions and Data Sources

Variable	Definition	Source
LDR	Loan-to-Deposit Ratio (%)	Financial Services Authority (OJK) Publication
LUSI	US Dollar Index	Federal Reserve Economic Data (FRED)
LCD	Foreign Exchange Reserves	*Indonesian Economic and Financial Statistics* Bank Indonesia Report
RASIO	Foreign Bank Assets / Total Bank Assets (%)	OJK Publication

4.2. Model specifications

To investigate the dynamic relationship between external economic variables and banking stability in Indonesia, this study employs the Vector Error Correction Model (VECM) framework. The VECM approach allows for the examination of both long-run equilibrium relationships and short-run dynamic adjustments among non-stationary but cointegrated variables (Johansen, 1988; Enders, 2015).

Following the empirical frameworks of Nguyen and Bui (2021), the model in this study is specified as follows:

$$\Delta LDR_t = \alpha_0 + \lambda(LDR_{t-1} - \beta_1 LUSI_{t-1} - \beta_2 LCD_{t-1} - \beta_3 RASIO_{t-1}) + \sum_{i=1}^{k} \gamma_{1i}\, \Delta LUSI_{t-i} + \sum_{i=1}^{k} \gamma_{2i} \Delta LCD_{t-i} + \sum_{i=1}^{k} \gamma_{3i} \Delta RASIO_{t-i} + \varepsilon_t \quad (1)$$

Where LDR_t is Loan to Deposit Ratio, $LUSI_t$ is US Dollar Index, LCD_t is Foreign Exchange Reserves, $RASIO_t$ is Ratio of Foreign Banks' Assets to Total Banking Assets, λ is error correction coefficient, which indicates the speed of adjustment toward long-run equilibrium, γ_i is short-run dynamic parameters capturing immediate responses among variables and ε_t is white noise disturbance term.

The term represents the cointegrating vector that captures the long-run equilibrium relationship among the variables. The sign and magnitude of the coefficient λ indicate how quickly the system corrects any disequilibrium from its long-run path.

4.3. Analysis stages

The analysis is carried out in several stages:

1. Stationarity Test: using the ADF and PP tests to ensure the stationarity properties of the data (Dickey & Fuller, 1979; Phillips & Perron, 1988).
2. Determination of Optimum Lag: determined using the AIC, SC, and HQ criteria according to the VAR/VECM procedure (Lütkepohl, 2005).
3. Johansen Cointegration Test: used to identify the number of long-term relationships between variables (Johansen, 1988).
4. VECM Model Estimation: produces cointegration vector coefficients (long run) and error correction term (ECT) as short run adjustment.
5. Impulse Response Function (IRF): used to observe the LDR response to shocks on the US Dollar Index, foreign exchange reserves, and the foreign bank asset ratio (Winarno et al., 2021).
6. Variance Decomposition (VD): used to measure the relative contribution of external variables to LDR fluctuations (Lütkepohl, 2005).
7. Granger Causality Test: used to identify the direction of the causal relationship between variables (Enders, 2015).

5. ANALYSIS RESULTS

5.1. DESCRIPTIVE STATISTICS

Table 3 presents the descriptive statistics of the variables used in the analysis. The Loan to Deposit Ratio (LDR) averages 83.25% over the sample period, with a standard deviation of 4.14, indicating relatively moderate fluctuations in banking intermediation during 2020-2024. The US Dollar Index exhibits greater dispersion, reflecting substantial movements in global dollar conditions throughout the observation period.

Table 3. Descriptive Statistics

Variable	Mean	Median	Std. Dev.	Minimum	Maximum
Loan-to-Deposit Ratio (LDR, %)	83.25	82.48	4.14	77.13	93.36
US Dollar Index	99,936.90	101,513.50	5,763.75	89,894.00	112,084.00
Foreign Bank Asset Ratio (%)	8.40	8.22	0.55	7.65	9.83
Foreign Exchange Reserves (Million US$)	138,698.11	137,607.03	6,427.15	120,968.88	155,719.38

Source: Author's calculation based on monthly data (2020-2024).

Foreign exchange reserves average USD 138.7 billion, with a relatively wide range, suggesting active reserve management in response to global financial volatility. In contrast, the foreign bank asset ratio shows comparatively low variability, indicating gradual structural adjustments in foreign bank penetration rather than abrupt shifts. Overall, the descriptive statistics suggest that while domestic banking stability remains relatively contained, external variables display greater volatility, justifying the use of dynamic time series techniques to capture both short term adjustments and long term equilibrium relationships.

5.2. Stationarity test results

Stationarity test is conducted to ensure the integration properties of the research variables, namely Loan to Deposit Ratio (LDR) , US Dollar Index (LUSI) , Foreign Exchange Reserves (LCD) , and the Ratio of Foreign Bank Assets to Total Commercial Bank Assets (RATIO) . Considering that economic and financial time series data are generally non-stationary at the level, testing is conducted up to the first difference stage using several methods, namely Levin, Lin & Chu (LLC) , Im, Pesaran and Shin (IPS) , as well as the Fisher panel test based on Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) .

The results of the stationarity test on the first difference are presented in Table 4.

Table 4. Stationarity Test Results (*First Difference*)

Method	Statistics	Probability	Conclusion
Levin, Lin & Chu t*	-13.2456	0.0000	Stationary
Im, Pesaran and Shin W-stat	-13.0019	0.0000	Stationary
ADF - Fisher Chi-square	129,544	0.0000	Stationary
PP - Fisher Chi-square	145,648	0.0000	Stationary

Source: Processed data, 2025.

Table 4 shows that all methods give consistent results. In the LLC test, a statistical value of -13.2456 with a probability of 0.0000 rejects the null hypothesis (H0) of the existence of a unit root, so that the research variables are stationary at first difference. The same result is shown by the IPS test with a statistical value of -13.0019 and a probability of 0.0000. Furthermore, the ADF-Fisher test produces a statistical value of 129.544 with a probability of 0.0000, while the PP-Fisher test produces a value of 145.648 with a probability of 0.0000, all of which confirm that the four variables are stationary at first difference. Thus, it can be concluded that all research variables, namely LDR, LUSI, LCD, and RATIO, are not stationary at the level, but become stationary after being differentiated once (I(1)) .

5.3. Results of determining optimal lag

Determining the optimal lag length is a critical step in estimating VAR and VECM models. The appropriate number of lags is necessary to adequately capture the dynamics between variables while avoiding model specification issues such as autocorrelation.

Table 5 presents the results of selecting the optimum lag based on several criteria, namely LR (Likelihood Ratio test), FPE (Final Prediction Error), AIC (Akaike Information Criterion), SC (Schwarz Information Criterion), and HQ (Hannan-Quinn Information Criterion).

Table 5. Results of Determining Optimal Lag

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-140.7563	NA	0.001730	4.991595	5.133694	5.046946
1	63.87361	373.9787*	2.59e-06*	-1.512883*	-0.802386*	-1.236130*
2	77.87310	23.65430	2.80e-06	-1.443900	-0.165004	-0.945744

Source: Processed data, 2025.

Based on Table 5, it can be seen that lag 1 was selected as the optimum lag by almost all criteria (LR, FPE, AIC, SC, and HQ). This indicates that lag 1 is most appropriate to describe the dynamics of the relationship between the Loan to Deposit Ratio (LDR), the US Dollar Index (LUSI), Foreign Exchange Reserves (LCD), and the Foreign Bank Asset

Ratio (RASIO). Although at lag 2 the AIC value is relatively close to lag 1, most other criteria do not support it, so the selection of lag 1 is more consistent and more appropriate for use in the model.

5.4. Model stability test

Before further VECM estimation, it is important to ensure that the model meets the stability requirements. Stability testing is performed using the roots of a characteristic polynomial , where the model is considered stable if all root values have a modulus less than one and lie within the unit circle. The stability test results are presented in Table 6.

Table 6. VECM Model Stability Test Results

Root	Modulus
0.959961 – 0.049797i	0.961252
0.959961 + 0.049797i	0.961252
0.837321	0.837321
0.339785	0.339785

Source: Processed data, 2025.

Based on Table 6, all roots have modulus values smaller than 1. The largest modulus value is 0.961252, while other modulus values are in the range of 0.83 and 0.33. This indicates that there are no roots outside the unit circle (modulus value greater than 1), so the model meets the stability conditions.

Meeting this stability condition is crucial because it is a prerequisite for the validity of VECM estimates. If any roots lie outside the unit circle, the model can become unstable and produce biased or inconsistent estimates (Lütkepohl, 2005; Enders, 2015).

These results provide confidence that the VECM model used in the study is suitable for use in subsequent analysis stages, including the estimation of long-term and short-term relationships, Granger causality tests, and Impulse Response Function (IRF) and Variance Decomposition (VD) analyses. Thus, the stability of the model ensures that the dynamics captured by the VECM can be trusted in representing the relationship between external variables (the US Dollar Index, foreign exchange reserves, and the foreign bank asset ratio) with the stability of banking intermediation (LDR) in Indonesia.

5.5. Johansen cointegration test

After ensuring first-order stationary data and determining the optimum lag, the next step is to conduct the Johansen cointegration test. This test is used to determine whether there is a long-term relationship between the variables in the model, namely the Loan to

Deposit Ratio (LDR), the US Dollar Index (LUSI), Foreign Exchange Reserves (LCD), and the Ratio of Foreign Bank Assets to Total Commercial Bank Assets (RATIO).

Testing is carried out using two main statistics, namely Trace Statistics and Maximum Eigenvalue Statistics. The test results are shown in Table 7 and Table 8.

Table 7. Results of the Johansen Cointegration Test (Trace Statistics)

Hypothesis No. of CE(s)	Eigenvalue	Trace Statistics	Critical Value (5%)	Prob.
None *	0.386967	52.68999	47.85613	0.0164
At most 1	0.240164	24.80433	29.79707	0.1877
At most 2	0.132597	8.375887	15.49471	0.4258
At most 3	0.002205	0.128020	3.841465	0.7205

Source: Processed data, 2025.

Table 8. Results of the Johansen Cointegration Test (Maximum Eigenvalue Statistic)

Hypothesis No. of CE(s)	Eigenvalue	Max-Eigen Statistics	Critical Value (5%)	Prob.
None *	0.386967	28.38156	27.58434	0.0395
At most 1	0.240164	15.92984	21.13162	0.2290
At most 2	0.132597	8.250567	14.26460	0.3538
At most 3	0.002205	0.128020	3.841465	0.7205

Source: Processed data, 2025.

Based on the results of the Johansen cointegration test on Trace Statistic (Table 7), it can be seen that the null hypothesis of no cointegration (None) is rejected at the 5% significance level because the Trace Statistic value (52.68999) is greater than the 5% critical value (47.85613) with a probability of 0.0164. However, in the at most hypothesis and so on, the Trace Statistic value is smaller than the 5% critical value, so the null hypothesis cannot be rejected. This result shows that there is one cointegration equation in the model.

Consistency is also shown by the Maximum Eigenvalue Statistic (Table 8), where the null hypothesis of no cointegration is rejected at the 5% significance level (Max-Eigen Statistic value = 28.38156 > 27.58434 with p-value = 0.0395). However, the hypothesis of at most 1 and so on is not rejected, which reaffirms that there is one cointegration equation.

These findings indicate that the LDR, US Dollar Index, Foreign Exchange Reserves, and Foreign Bank Asset Ratio variables have a stable long-term relationship. In other words, despite short-term fluctuations, there is a long-term equilibrium mechanism between external factors and the stability of banking intermediation in Indonesia.

The existence of this cointegration relationship indicates that the Vector Error Correction Model (VECM) is suitable for use in this study. Through the VECM, not only can short-term relationships between variables be analyzed, but also the adjustment process towards long-term equilibrium can be studied (Johansen, 1991; Enders, 2015).

5.6. VECM estimation results

After all tests before that demonstrate the feasibility of using the model, the next step is to estimate the Vector Error Correction Model (VECM). This estimation aims to identify the long-term and short-term relationships between external variables (US Dollar Index/LUSI, Foreign Exchange Reserves/LCD, and Foreign Bank Asset Ratio/RASIO) with the stability of banking intermediation in Indonesia as measured by the Loan to Deposit Ratio (LDR).

Long-term estimation results show that (Table 9):

1. The US Dollar Index (LUSI) has a negative and significant effect on the LDR, with a coefficient of -27,325.36. This means that USD appreciation tends to reduce banking intermediation capacity in Indonesia.
2. Foreign Exchange Reserves (LCD) also had a negative and significant effect on the LDR (-34,272.14). This suggests that increasing foreign exchange reserves is associated with reduced pressure on the financial system, leading banks to adjust their intermediation function.
3. The Foreign Bank Asset Ratio (RASIO) has a significant negative effect on the LDR (-2,314.175). The presence of foreign banks with a larger asset proportion has the potential to intensify competition and influence domestic banks' intermediation strategies.

Table 9. VECM Estimation Results

Variables	Coefficient	Std. Error	t-Statistic	Information
Cointegration Equation (Long Run)				
LDR(-1)	1,000,000	–	–	-
LUSI(-1)	-27325.36	4634.44	-5.89615	Significant (5%)
LCD(-1)	-34272.14	6413.44	-5.34380	Significant (5%)
RATIO(-1)	-2314.175	307,291	-7.53088	Significant (5%)
Constant	323928.8	–	–	–
Error Correction Term (ECT) and Short-Term Dynamics				
COINTEQ1 → D(LDR)	0.063124	0.03060	2.06284	Significant
COINTEQ1 → D(LUSI)	4.73E-06	3.9E-06	1.20508	Not significant
COINTEQ1 → D(LCD)	5.13E-06	4.5E-06	1.13596	Not significant
COINTEQ1 → D(RATIO)	0.000223	6.3E-05	3.53556	Significant

Source: Processed data, 2025.

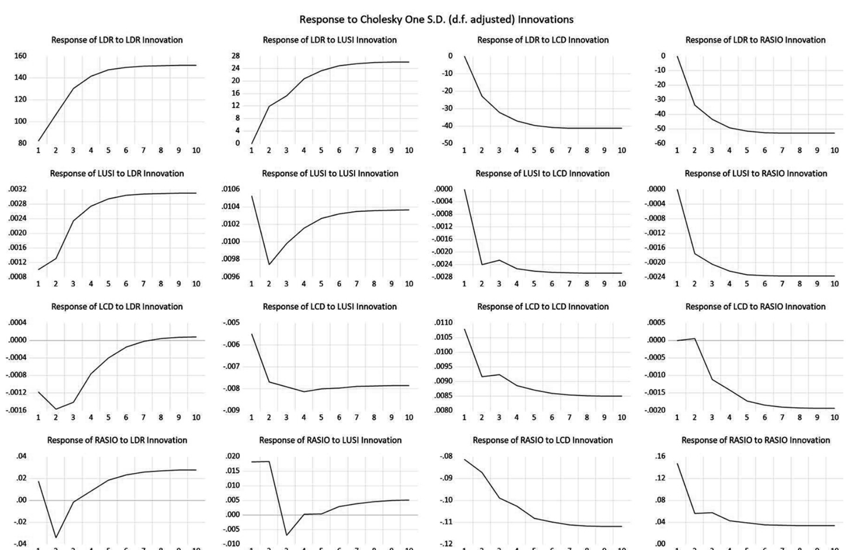
Overall, these results indicate that the three external variables have a long-term relationship with the stability of banking intermediation in Indonesia.

In the short run, the Error Correction Term (ECT) is significant for the ΔLDR and ΔRATIO equations:

1. The ECT coefficient for ΔLDR is 0.063124 with a t-statistic of 2.06284, which is significant at the 5% level. The positive and significant adjustment coefficient in the ΔLDR equation suggests that deviations from the long-run equilibrium are not corrected monotonically. Instead, the banking intermediation ratio exhibits short-run amplification dynamics, implying that external shocks may initially intensify liquidity imbalances before gradual stabilization through broader system dynamics.
2. The ECT coefficient for ΔRATIO is 0.000223 ($t = 3.53556$), which is also significant, indicating that the role of foreign banks contributes to the dynamics of adjustment towards equilibrium.
3. The ECT on ΔLUSI and ΔLCD is insignificant, which means that shocks to the USD Index and foreign exchange reserves do not directly affect short-term dynamics, but their impact is more dominant in the long term.

The Impulse Response Function (IRF) is used to trace the response of variables to shocks of one standard deviation from other variables in the VECM system. This analysis is important to understand the direction, intensity, and duration of the influence of external variables (US Dollar Index/LUSI, Foreign Exchange Reserves/LCD, and Foreign Bank Asset Ratio/RATIO) on banking stability as measured by the Loan to Deposit Ratio (LDR) (Figure 1).

Figure 1. Results of Impulse Response Function (IRF) Between Variables in VECM



Source: Processed data, 2025.

5.7. LDR response to external variable shock

LDR Response to LUSI (US Dollar Index)

The LDR responded positively to the LUSI shock. The response increased sharply in the initial period (1–5) and then stabilized at a higher level. This indicates that USD appreciation leads to an increase in the LDR, which can be interpreted as an incentive for banks to expand intermediation when exchange rate pressures increase.

LDR Response to LCD (Foreign Exchange Reserves)

The LDR response to the foreign exchange reserve shock was significantly negative. The LDR declined drastically until the third period before stabilizing at a lower level. This means that the increase in foreign exchange reserves is associated with a decline in the bank intermediation function, which may be related to increased external liquidity, reducing the need for domestic credit distribution.

LDR Response to RATIO (Foreign Bank Assets)

The LDR also responded negatively to shocks to the RATIO, particularly in the initial period, before stabilizing at a lower level after period 5. This suggests that the expansion of foreign bank assets may put pressure on domestic banking intermediation.

External Variable Response to LDR Shock

LUSI on LDR

Positive response with a steady increase from the initial period to the 6th period, then reaching a balance point. This shows the link between the domestic intermediation function and global exchange rate pressures.

LCD on LDR

The initial response was negative before gradually turning positive, albeit by a small amount. This indicates that domestic intermediation has only a limited effect on the dynamics of foreign exchange reserves.

RATIO to LDR

Negative responses in the initial period and only increased slightly after the 5th period, although they remained at a low level. This confirms that the intermediary role of domestic banks is relatively weak in influencing the competitive position of foreign banks.

Internal Response between External Variables

LUSI on LCD and RATIO showed a significant negative pattern, indicating that USD appreciation tends to suppress foreign exchange reserves and the portion of foreign bank assets. LCD on LUSI and RATIO showed a negative response at the beginning of the period, which then stabilized near zero, indicating that the relationship between foreign exchange reserves and other external variables is more dominant in the short term. RATIO on LUSI and LCD shows a negative response that continues into the medium term, indicating that external fluctuations have implications for the dynamics of foreign banks in the Indonesian financial system.

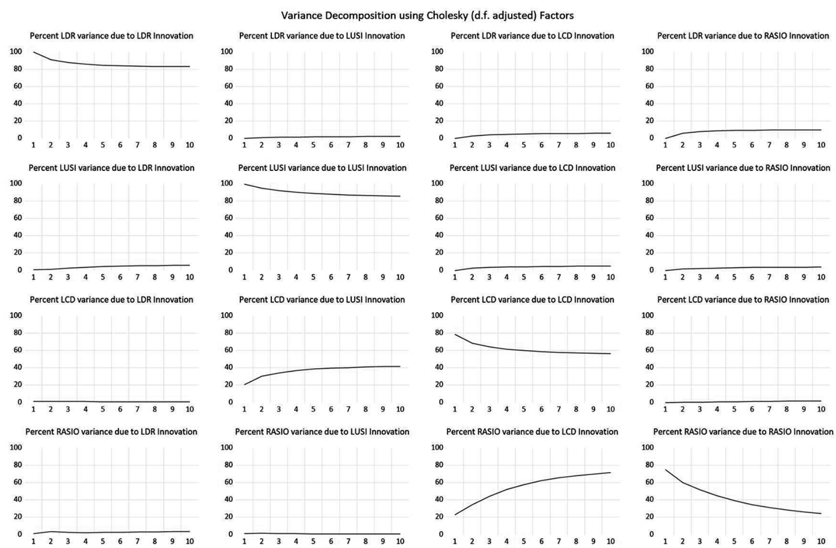
The results of the IRF confirm that external variables have a significant influence on the stability of banking intermediation in Indonesia. The shock to the US Dollar Index drove an increase in the LDR, while the shock to Foreign Exchange Reserves and the Foreign Bank Asset Ratio actually suppressed the intermediation function. The LDR response to external variables is relatively fast (1–3 periods) before reaching stability, which indicates the short-term vulnerability of the banking sector to external shocks.

This finding is in line with previous literature showing that financial openness makes domestic banking more vulnerable to external dynamics (Alper and Yilmaz, 2021; Park & Shin, 2020). Thus, the IRF results strengthen the evidence that the resilience of banking intermediation in Indonesia is greatly influenced by global conditions, particularly exchange rate fluctuations and international liquidity dynamics.

5.8. Variance decomposition (VD)

Variance Decomposition (VD) provides information on the proportion of a variable's variation explained by shocks to itself and shocks to other variables in the model. In other words, VD complements IRF analysis by showing the relative contribution of each variable in explaining short-term to long-term fluctuations (Figure 2).

Figure 2. Results of Variance Decomposition Between Variables in VECM



Source: Processed data, 2025.

Variance Decomposition (VD) provides an overview of the proportion of a variable's variation explained by its own shocks and shocks from other variables. The analysis results in Figure 2 show that the variation in the Loan to Deposit Ratio (LDR) in the initial period was almost entirely explained by its own shocks, approaching 100 percent. However, as the period progressed, this proportion decreased slightly to around 85 to 90 percent, while the influence of external variables such as the US Dollar Index (LUSI), Foreign Exchange Reserves (LCD), and the Foreign Bank Asset Ratio (RASIO) began to contribute, although on a relatively small scale, namely below 15 percent cumulatively. This finding indicates that the stability of banking intermediation in Indonesia, as measured by the LDR, is largely determined by internal domestic factors, although external factors still play an additional role.

Meanwhile, LUSI variation is dominated by its own shocks, which account for more than 90 percent of the observation period, while the contribution of other variables, including LDR, LCD, and RATIO, remains very limited, accounting for less than 10 percent. This confirms that the dynamics of the global exchange rate, as represented by the US Dollar Index, are more influenced by global external factors than by domestic banking conditions in Indonesia.

In contrast to LUSI, variations in the LCD exhibit a more dynamic pattern. In the initial period, approximately 70 to 80 percent of the variation in foreign exchange reserves was explained by internal shocks. However, in the medium to long term, the contribution from LUSI increased to approximately 30 percent. This fact confirms that Indonesia's foreign exchange reserves are highly sensitive to global exchange rate fluctuations. On the other hand, the contribution of the LDR and RATIO to the variation in foreign exchange reserves was relatively small and insignificant throughout the period.

As for the RATIO, in the initial period, its variation was largely explained by internal shocks, accounting for around 80 percent. However, in the medium term, the contribution from LCD gradually increased to around 30 percent, indicating that foreign exchange reserves play a significant role in explaining the movement of foreign bank assets in Indonesia. Furthermore, the LUSI (Low Debt to Deposit Ratio) also had a relatively small effect on RATIO variation, while the LDR (Low Debt to Deposit Ratio) did not have a significant effect.

Overall, the results of this Variance Decomposition confirm that the stability of banking intermediation in Indonesia remains highly dependent on internal factors. However, external factors, particularly global exchange rate fluctuations as reflected in the US Dollar Index and foreign exchange reserves, play a significant role in the medium to long term. The close relationship observed between foreign exchange reserves and the foreign bank asset ratio also demonstrates that foreign banking stability in Indonesia is closely linked to the national foreign exchange reserve position, which serves as a liquidity cushion against potential external shocks. These findings emphasize that strengthening domestic fundamentals remains a top priority in maintaining banking stability, alongside vigilance against external dynamics that could potentially impact the national financial system.

5.9. Granger causality test

The Granger causality test was conducted to identify the direction of the causal relationship between external variables (LUSI, LCD, RATIO) and domestic banking stability (LDR). The test results are shown in Table 10.

Table 10. Granger Causality Test Results

Null Hypothesis	F-Statistic	Prob.	Results
LUSI does not Granger Cause LDR	2.31024	0.1092	Not significant
LDR does not Granger Cause LUSI	1.09316	0.3426	Not significant
LCD does not Granger Cause LDR	4.86512	0.0115	Significant (LCD → LDR)
LDR does not Granger Cause LCD	0.34992	0.7064	Not significant
RATIO does not Granger Cause LDR	7.24241	0.0017	Significant (RATIO → LDR)
LDR does not Granger Cause RATIO	1.34622	0.2690	Not significant
LCD does not Granger Cause LUSI	4.46910	0.0161	Significant (LCD → LUSI)
LUSI does not Granger Cause LCD	0.82612	0.4433	Not significant
RATIO does not Granger Cause LUSI	4.10623	0.0220	Significant (RATIO → LUSI)
LUSI does not Granger Cause RATIO	0.17284	0.8417	Not significant
RATIO does not Granger Cause LCD	0.57971	0.5636	Not significant
LCD does not Granger Cause RATIO	0.56192	0.5735	Not significant

Source: Processed data, 2025.

The test results show several significant causal relationships. First, there is a one-way causality from foreign exchange reserves (LCD) to the Loan to Deposit Ratio (LDR), with a probability value of 0.0115 which is significant at the 5 percent level. This indicates that changes in foreign exchange reserves can affect the banking intermediation function in Indonesia, but not vice versa. Second, the foreign bank asset ratio (RATIO) is also proven to significantly affect the LDR (p-value = 0.0017), which indicates that the presence of foreign banks affects the stability of domestic banking, especially in credit distribution and fund raising.

In addition, a one-way causality was found from LCD to LUSI (p-value = 0.0161), which means that the dynamics of foreign exchange reserves can affect the movement of the US Dollar Index. This is in line with the view that international capital and liquidity flows can affect global exchange rates through the role of foreign exchange reserves. Another important finding is the causal relationship of RATIO to LUSI (p-value = 0.0220), which indicates the role of foreign bank assets in influencing the dynamics of global exchange rates in Indonesia.

On the other hand, no evidence of causality was found from LDR to external variables, either to LUSI, LCD, or RATIO. These results strengthen the conclusion that domestic banking stability is more influenced by external factors than vice versa.

Overall, the Granger causality test results confirm that external factors, particularly foreign exchange reserves and the foreign bank asset ratio, play a dominant role in influencing the stability of banking intermediation in Indonesia. Meanwhile, the LDR's influence on external dynamics is relatively insignificant. This finding is in line with previous literature that emphasizes the importance of global factors and the country's external position in maintaining the stability of the domestic banking sector (Claessens and van Horen, 2015; Eichengreen, 2019).

5.10. Robustness checks

To ensure that the baseline VECM findings are not driven by temporary structural shocks, proxy selection or sample segmentation bias, several alternative specifications are estimated. These include the introduction of a COVID 19 dummy variable and the replacement of LDR with NPL as an alternative banking stability indicator. The results provide a deeper understanding of the structural stability of the macro banking nexus (Table 11).

Table 11. Robustness Results with Covid-19 Dummy Variable

Variable	Coefficient	t-Statistic
LUSI(-1)	455.9586	2.0991
LCD(-1)	-857.3675	-3.4028
RASIO(-1)	-60.0783	-3.9876
DUMMY(-1)	79.1505	5.2170
Error Correction Term (ΔLDR): -0.020340 (t = -2.4421)		

Source: Processed data, 2025.

The inclusion of a pandemic dummy variable (equal to 1 for 2020M03–2021M12 and 0 otherwise) allows the model to explicitly control for an extraordinary structural shock affecting both macroeconomic activity and banking behavior. The long-run cointegration equation remains statistically significant after controlling for the dummy. LUSI (455.9586; t = 2.0991), LCD (-857.3675; t = -3.4028), and RASIO (-60.0783; t = -3.9876) preserve their statistical relevance, indicating that the structural relationship between macroeconomic conditions and banking liquidity is not eliminated once the pandemic shock is isolated. Importantly, the dummy variable itself is highly significant (79.1505; t = 5.2170), confirming that the pandemic generated a discrete upward shift in the long-run equilibrium level of LDR.

Despite this shift, the error correction term in the ΔLDR equation remains negative and statistically significant (ECT = -0.020340; t = -2.4421), indicating continued convergence toward long-run equilibrium at a monthly adjustment speed of approximately 2%. This result is crucial because it shows that while COVID 19 altered the equilibrium level, it did not dismantle the equilibrium mechanism itself. In other words, the pandemic acted as a level shock rather than a structural break in the long-run relationship. This specification therefore strengthens the baseline findings by demonstrating that the long-run macro–banking linkage survives the inclusion of an explicit crisis control.

To examine whether the results are dependent on the choice of banking indicator, LDR is replaced with Non-Performing Loans (NPL), which captures credit risk rather than liquidity conditions (Table 14). The cointegration equation under this specification shows that LUSI (13.5297; t = 7.0862) and LCD (11.0031; t = 4.3657) remain highly significant, while RASIO becomes statistically insignificant (0.001573; t = 0.0136). This indicates that macroeconomic conditions exert a strong long-run influence on banking credit risk, even if capital adequacy plays a weaker direct role in this alternative formulation.

Table 14 Alternative Dependent Variable: NPL

Variable	Coefficient	t-Statistic
LUSI(-1)	13.5297	7.0862
LCD(-1)	11.0031	4.3657
RASIO(-1)	0.001573	0.0136
Error Correction Term (ΔNPL): -0.890769 (t = -33.9955)		

Source: Processed data, 2025.

Most strikingly, the error correction term in the ΔNPL equation is extremely large and highly significant (ECT = -0.890769; t = -33.9955). This implies a rapid speed of adjustment, with nearly 89% of disequilibrium corrected within one month. Economically, this suggests that credit risk adjusts far more aggressively to macroeconomic imbalances than liquidity ratios do. While LDR reflects balance sheet positioning behavior, NPL captures realized credit deterioration, which may respond more sharply to macro shocks. The substitution exercise therefore confirms that the macroeconomic determinants affect both liquidity and credit risk channels. The persistence of cointegration under an alternative proxy reduces concerns of indicator-specific bias and enhances the structural validity of the empirical framework.

These robustness exercises collectively indicate that the estimated long-run relationships are not driven by temporary crisis effects, proxy-specific bias, or sample segmentation, but instead reflect a structurally persistent macro banking equilibrium mechanism.

5.11. Discussion

Long-Term Relationship between the US Dollar Index, Foreign Exchange Reserves, Foreign Bank Asset Ratio, and Banking Stability (LDR)

The VECM estimation results show that in the long run, the US Dollar Index (LUSI), foreign exchange reserves (LCD), and the foreign bank asset ratio (RASIO) have a significant relationship with banking stability in Indonesia, proxied by the Loan to Deposit Ratio (LDR). The long-term coefficients indicate that an increase in the US Dollar Index, a decline in foreign exchange reserves, and an increase in the proportion of foreign bank assets are associated with a deterioration in domestic banking intermediation. This finding is consistent with the theoretical framework suggesting that external shocks and foreign bank penetration may increase financial vulnerability in developing countries (Claessens and van Horen, 2015).

Importantly, the robustness analysis confirms that this long-run relationship is not driven solely by the COVID-19 crisis period. When a pandemic dummy variable is introduced to explicitly control for the structural shock during 2020–2021, the cointegrating relationship remains statistically significant. Although the dummy variable captures a discrete upward shift in the equilibrium level of LDR, the macroeconomic variables retain their long-run relevance. This indicates that the pandemic acted as a level shock rather than a structural break in the macro–banking nexus.

Findings regarding the US Dollar Index indicate that US dollar appreciation is associated with a contraction in banking intermediation. This is consistent with Avdjiev, et al. (2019), who found that a strengthening US dollar tightens global financial conditions and reduces lending in emerging markets. In Indonesia, dependence on international capital flows amplifies this transmission mechanism, reinforcing the vulnerability of domestic liquidity conditions to global dollar cycles.

Meanwhile, foreign exchange reserves play a stabilizing role. The negative long-term relationship between LCD and LDR suggests that declining reserves weaken banking intermediation. This aligns with Aizenman and Sun (2012), who emphasize the buffer-stock function of reserves in mitigating sudden stops and capital flow volatility. Adequate reserve accumulation therefore strengthens market confidence and enhances systemic resilience.

Furthermore, the foreign bank asset ratio exhibits a significant long-run effect on LDR, indicating that deeper foreign bank penetration may alter the structure of domestic intermediation. While this supports Cull and Martínez Pería (2013), who document crowding-out effects in developing markets, it also highlights the importance of regulatory quality, as emphasized by Claessens and van Horen (2012).

The substitution of LDR with Non-Performing Loans (NPL) as an alternative stability proxy further strengthens the structural interpretation. The persistence of cointegration under the NPL specification indicates that macroeconomic fundamentals influence not only liquidity positioning but also credit risk dynamics. Notably, the substantially larger error correction coefficient in the NPL model suggests that credit risk adjusts more rapidly to macroeconomic disequilibria than liquidity ratios. This distinction implies the presence of multiple transmission channels—liquidity and credit-risk—through which external shocks propagate within the banking system.

Thus, the findings confirm a structurally persistent long-run relationship between external variables and domestic banking stability, which remains intact even after controlling for crisis effects and alternative stability proxies.

Short-Term Dynamics between the US Dollar Index, Foreign Exchange Reserves, Foreign Bank Asset Ratio and Banking Stability

The short-term dynamics indicate heterogeneous adjustment behavior. In the full-sample estimation, the error correction term (ECT) in the LDR equation is statistically significant, indicating convergence toward long-run equilibrium following short-term disequilibria.

In the short term, the LUSI's influence on the LDR tends to be unstable and fluctuating. The IRF results support the estimate, indicating that shocks to the US Dollar Index will increase pressure on banking liquidity, which in turn weakens the intermediation function. This is in line with research by Kalemli-Ozcan et al. (2013), which found that US dollar exchange rate volatility is a key determinant of global risk transmission to the domestic financial sector, including banking.

Foreign exchange reserves (LCD) have a relatively limited but still significant impact on the LDR over a specific time horizon. This reflects the role of foreign exchange reserves as a buffer, the effects of which only become apparent after a certain period. Aizenman et al. (2015) also found that foreign exchange reserves have a more dominant influence in dampening long-term volatility, while in the short-term, their function is more focused on maintaining market confidence.

Meanwhile, the foreign bank asset ratio (RATIO) shows a significant influence in the short term on LDR. The VECM and IRF results confirm that increased foreign bank penetration immediately depresses domestic bank intermediation performance. This finding is consistent with Ghosh et al. (2014), who stated that the role of foreign banks in emerging markets often increases the vulnerability of the banking system to external shocks, particularly in the short term. However, this crowding-out effect has the potential to diminish in the long term if the domestic financial system successfully undergoes structural adaptation.

Thus, the short-term dynamics of the three independent variables indicate that Indonesian banking stability remains vulnerable to external shocks, particularly from fluctuations in the US Dollar Index and the dominance of foreign banks. Foreign exchange reserves serve more as a long-term buffer, although their initial effect is limited. Therefore, monetary and macro prudential policies responsive to global volatility are crucial to maintaining the stability of the banking intermediation function in the short term.

The Impact of External Shocks on Banking Stability

The Impulse Response Function *(*IRF*)* analysis show that the Loan-to-Deposit Ratio (LDR) responds significantly to shocks from external variables, although in varying directions and intensities. Shocks to the US Dollar Index (LUSI) tend to suppress the banking intermediation function, as evidenced by the decline in the LDR in the initial periods before eventually stabilizing. This confirms that a strengthening US dollar tightens domestic liquidity, reduces credit capacity, and weakens banking intermediation. This finding is consistent with Avdjiev et al. (2019), who found that global US dollar appreciation worsens the financial conditions of emerging market countries through a contraction in cross-border lending.

Meanwhile, shocks to foreign exchange reserves (LCD) elicit a positive response from the LDR, indicating that increased foreign exchange reserves strengthen the intermediation function. With sufficient foreign exchange reserves, domestic banks are more resilient to external pressures, allowing them to continue disbursing credit stably. This finding aligns with Aizenman and Hutchison (2012), who demonstrated that foreign exchange reserves serve as a buffer against external financial shocks, thereby strengthening the stability of the domestic financial sector.

In contrast to the two previous variables, shocks to the foreign bank asset ratio (RATIO) have a negative impact on the LDR, meaning that the penetration of foreign bank assets has the potential to reduce the ability of domestic banks to carry out their intermediation function. This can be caused by the crowding out effect, where the presence of foreign banks dominates the market and suppresses the room for domestic banks to operate. These findings align with research by Cull and Martínez Pería (2013), who found that foreign bank expansion in developing countries often reduces the role of domestic banks in credit distribution, particularly during periods of global uncertainty. However, these findings also echo the alternative argument of Claessens and van Horen (2014), who argued that the presence of foreign banks can enhance stability if domestic regulations are strong and policy coordination is effective.

The Variance Decomposition (VD) results show that although the LDR variation is still dominated by its own contribution, the proportion of contributions from LUSI, LCD, and RATIO increases gradually in the medium to long term. This reinforces the finding that external shocks, although initially temporary, have a significant cumulative role in domestic banking stability. Thus, the stability of banking intermediation in Indonesia is highly vulnerable to external shocks, particularly from the global exchange rate (LUSI) and foreign bank dominance (RATIO), while foreign exchange reserves serve as an important mitigation instrument.

Overall, this study confirms that the impact of external shocks cannot be ignored in maintaining banking stability. Therefore, policies that emphasize strengthening foreign exchange reserves, stabilizing the exchange rate, and appropriate regulation of the role of foreign banks are key to strengthening the banking intermediation function in Indonesia.

Direction of Causality between External Variables and Banking Stability

The results of the Granger causality test indicate that the relationship between external variables and banking stability (LDR) in Indonesia is not symmetrical, but rather dominated by a one-way causal relationship. First, a causal relationship was found from foreign exchange reserves (LCD) to LDR , but not vice versa. This means that changes in foreign exchange reserves have been shown to influence the dynamics of domestic banking intermediation, but LDR fluctuations have no significant impact on changes in foreign exchange reserves. This is in line with the findings of Aizenman, Jinjarak and Park (2011), who stated that foreign exchange reserves function as a stabilization instrument against external shocks, making them more exogenous to the domestic financial system.

Second, there is a one-way causal relationship from the foreign bank asset ratio (RATIO) to LDR, which indicates that increasing foreign bank penetration affects domestic banking stability, but the stability of banking intermediation does not directly affect the proportion of foreign bank assets. These findings support research by Cull and Martínez Pería (2013), who found that foreign bank expansion in developing countries can influence domestic bank lending patterns. However, these results also differ from the study by Claessens and van Horen (2014), who found that the presence of foreign banks in some countries actually strengthens stability if the regulatory infrastructure is strong and external risks are minimized.

Third, in terms of interactions between external variables, the causality test found an effect of LCD on the US Dollar Index (LUSI) and of RATIO on LUSI. This indicates that foreign exchange reserves and foreign bank penetration contribute to the dynamics of US dollar exchange rate movements in Indonesia, although the reverse direction was not proven significant. This finding is relevant to the research of Kalemli-Ozcan et al. (2013), which emphasized that international capital flows and global banking activity play a role in strengthening the transmission of exchange rate shocks to the domestic market.

Overall, these results confirm that banking stability in Indonesia is more influenced by external variables (LCD and RATIO), while the US Dollar Index does not directly affect the LDR in the short term through a causal mechanism. This pattern highlights the importance of foreign exchange reserves and supervision of foreign bank activities as key factors in maintaining the resilience of the banking intermediation system. Thus, the identified direction of causality supports the view that external factors are more determinant than endogenous in explaining domestic banking stability.

6. Conclusions and Policy Recommendations

6.1. Conclusion

This study analyzes the relationship between external variables (the US Dollar Index, foreign exchange reserves, and the foreign bank asset ratio) and banking stability in Indonesia, proxied by the Loan-to-Deposit Ratio (LDR), using the Vector Error Correction Model (VECM) approach. Four main findings can be concluded.

First, in the long term, the US Dollar Index, foreign exchange reserves, and the foreign bank asset ratio have been shown to significantly influence the stability of banking intermediation. A strengthening US dollar and the increasing dominance of foreign bank assets suppress the intermediation function, while foreign exchange reserves play a positive role in maintaining banking resilience.

Second, in the short term, LDR dynamics exhibit high sensitivity to external shocks, particularly the US dollar exchange rate and the role of foreign banks. Meanwhile, foreign exchange reserves exhibit a stronger stabilizing effect in the long term, although its short-term impact is relatively limited.

Third, the IRF and Variance Decomposition results confirm that shocks from the US Dollar Index and the foreign bank asset ratio tend to lower the LDR, while shocks from foreign exchange reserves strengthen the intermediation function. Although variations in the

LDR are largely explained by its own contribution, the role of external variables increases significantly over the medium to long horizon.

Fourth, the Granger causality test results indicate a one-way causality from foreign exchange reserves and the foreign bank asset ratio to the LDR. This indicates that external factors are more determinant than endogenous in explaining domestic banking stability, while the LDR's influence on external factors is relatively insignificant.

Overall, the results of this study confirm that the stability of banking intermediation in Indonesia is strongly influenced by external factors, both through global exchange rate channels and foreign bank penetration, with foreign exchange reserves as a key instrument for risk mitigation.

6.2. Policy recommendations

The findings of this study have several important policy implications. First, strengthening foreign exchange reserves should be a monetary policy priority, as adequate reserves have been shown to reduce banking vulnerability to external shocks and maintain the intermediation function. Second, monetary and macro prudential authorities need to respond proactively to US Dollar Index volatility through more flexible exchange rate policies and domestic liquidity stabilization instruments.

Third, supervision and regulation of foreign banks need to be strengthened. Although the presence of foreign banks has the potential to increase efficiency, the results of this study indicate that excessive penetration can reduce the space for domestic banking intermediation. Therefore, policies that balance the role of foreign banks with protecting systemic stability are very important.

Fourth, coordination between Bank Indonesia, the Financial Services Authority, and the government in macro prudential and fiscal policies needs to be strengthened, considering that domestic banking stability is heavily influenced by external factors. This policy integration can strengthen the resilience of Indonesia's financial system to global shocks.

While the empirical findings suggest strengthening foreign exchange reserves and calibrating the role of foreign banks, the feasibility of these recommendations must be assessed within Indonesia's macroeconomic and regulatory constraints. Reserve accumulation is not costless, as it involves sterilization costs, fiscal coordination challenges, and exposure to global monetary cycles, particularly those driven by the Federal Reserve. However, Indonesia's institutional framework provides sufficient policy space for dynamic reserve management. Bank Indonesia has implemented a multi-instrument exchange rate stabilization strategy, including spot market intervention, domestic non-deliverable forwards, and government bond market operations, which allows reserve management without excessive distortion.

Similarly, regulating foreign bank penetration does not imply restricting financial openness. Indonesia remains committed to international financial integration and WTO obligations. Nevertheless, macro prudential supervision under the Financial Services Authority (OJK) provides tools to manage systemic exposure, including capital adequacy requirements, liquidity coverage ratios, and countercyclical buffers. The recommendation therefore concerns prudential calibration rather than protectionist intervention. In this context, the policy implications derived from this study are feasible when they are implemented within a coordinated macro–financial policy framework rather than as isolated measures.

Thus, this study provides an empirical contribution to the literature on banking stability in developing countries and offers relevant policy recommendations to maintain the intermediation function of Indonesian banking amidst increasingly complex global dynamics.

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