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CONSEIL NATIONAL
DE LA PRODUCTIVITÉ

LA PRODUCTIVITÉ – UN MOTEUR
DE LA COMPÉTITIVITÉ

CONSEIL NATIONAL
DE LA PRODUCTIVITÉ
LUXEMBOURG

Les opinions exprimées dans ce rapport sont celles des membres du Conseil national de la productivité et celles des auteurs des études respectives.

Pour toute requête ou suggestion, contactez le secrétariat du Conseil national de la productivité.

Ministère de l'Économie
Observatoire de la compétitivité
19-21 Boulevard Royal
L-2449 Luxembourg
observatoire@eco.etat.lu

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Ont contribué à l'élaboration de cette publication :

Conseil national de la productivité
Serge ALLEGREZZA
Jean-Claude REDING
Michel WURTH
Arnaud BOURGAIN
Patrick LENAIN
Aline MULLER
Marc NIEDERKORN
Chiara PERONI
Paul SCHOSSELER

Ministère de l'Économie - Observatoire de la compétitivité
Secrétariat du Conseil national de la productivité
Max JENTGEN
Charel THILL

Institut national de la statistique et des études économiques (STATEC)
STATEC Research
Golnaz AMJADI
Xi CHEN
Charles-Henri DIMARIA
Giovanni MANGIAROTTI
Chiara PERONI

Table des matières

Partie 1

Les réflexions et analyses macroéconomiques du Conseil national de la productivité

La première partie du rapport 2022-2023 du Conseil national de la productivité (CNP) présente d'abord quelques réflexions et constats du CNP. Elle comprend ensuite une série d'analyses descriptives macroéconomiques sur la productivité du travail ainsi que la contribution des facteurs de production et de la productivité multifactorielle sur l'évolution de la productivité et la croissance économique. Cette partie est complétée par des analyses sur la productivité des ressources et de l'énergie.

1.1

Réflexions du CNP

La Conseil national de la productivité (CNP) constate que l'évolution médiocre de la productivité du travail persiste au niveau agrégé de l'économie nationale. Vu son importance pour conforter la compétitivité des entreprises, soutenir l'évolution des salaires réels, pérenniser le modèle socioéconomique et accroître le niveau de vie à long terme, le CNP réitère sa recommandation de faire de la productivité une priorité de l'agenda politique, du débat public et de la recherche académique. Pour réaliser les gains de productivité escomptés, l'action devra porter sur deux niveaux. D'une part, il est essentiel d'augmenter la frontière productive et, d'autre part, il s'agit d'aider les entreprises à se rapprocher de la frontière productive, tout en poursuivant la voie de la double transition écologique et numérique de l'économie luxembourgeoise.

La productivité multifactorielle reste le principal contributeur à l'évolution de la productivité du travail. Pour relancer la productivité, il est nécessaire d'augmenter l'efficience globale avec laquelle les facteurs travail et capital sont conjointement utilisés dans le processus de production. Dans ce contexte, la recherche et développement (R&D) et l'innovation, le renforcement et la reconversion des compétences de la main-d'œuvre, l'amélioration de la gouvernance d'entreprise et des compétences managériales ainsi que l'assouplissement continu du cadre réglementaire restent des domaines d'action prioritaires aux yeux du CNP. Une réglementation moins restrictive facilitant l'entrée et la sortie des entreprises du marché devrait augmenter les pressions concurrentielles, améliorer l'efficience allocative et affermir ainsi l'évolution de la productivité. En complément, des efforts sont nécessaires pour favoriser l'intégration du progrès technologique et l'adoption des meilleures pratiques dans les entreprises.

Les analyses montrent un impact positif de l'approfondissement du capital sur la productivité du travail et la croissance économique. Ce constat vaut aussi bien pour le capital tangible que pour le capital intangible. En conséquence, le CNP invite tous les acteurs, privés et publics, à poursuivre une politique d'investissement ambitieuse.

Au vu des différences qui existent non seulement entre les secteurs, mais également au sein des secteurs, où des études mettent en évidence un écart grandissant entre les entreprises les plus productives et les entreprises les moins productives, des politiques différenciées s'imposent afin de relancer la productivité. Il s'agit plus exactement de conjuguer les actions en faveur des déterminants généraux de la productivité avec les besoins spécifiques des différentes activités économiques.

Au cours des dernières années, le CNP a réalisé une multitude d'analyses et d'études pour éclaircir les différentes facettes de la productivité. Dans une prochaine étape, il s'agit d'étoffer les études réalisées et de consolider les connaissances acquises jusqu'ici. Le CNP entend également renforcer ses efforts de communication afin de mieux alimenter le débat politique et public et de rendre la matière plus accessible pour un plus grand nombre d'intéressés. Finalement, le CNP envisage de mettre en avant les leçons à tirer et de traduire les constats en actions et recommandations concrètes pour relancer la productivité de l'économie luxembourgeoise.

1.2
Analyses macroéconomiques

Ce chapitre propose des analyses macroéconomiques sur différents aspects de la productivité, à savoir la productivité du travail et la productivité multifactorielle ainsi que la productivité des ressources et celle de l'énergie. Les analyses ont été réalisées par l'Observatoire de la compétitivité (dans sa fonction de secrétariat du CNP) et se basent sur des données et statistiques publiques de l'Organisation de coopération et de développement économiques (OCDE), d'Eurostat et de l'Institut national de la statistique et des études économiques du Grand-Duché de Luxembourg (STATEC). Les analyses couvrent la période de 2010 à 2022.

Les répercussions des crises successives, notamment la pandémie de COVID-19, les tensions géopolitiques accrues, la guerre d'agression russe en Ukraine et le conflit actuel au Proche-Orient ainsi que la flambée générale des prix contrée par la hausse des taux directeurs des Banques centrales afin de contenir l'inflation, ont continué à peser lourd sur l'activité et les perspectives économiques au Luxembourg et ailleurs. Le PIB (1,4 %) et l'emploi (3,4 %) ont certes augmenté au Luxembourg en 2022, mais les perspectives conjoncturelles se sont assombries depuis. Dans ses prévisions économiques de l'automne 2023[1], la Commission européenne prédit pour le Luxembourg une baisse du PIB de -0,6 % en 2023 et table sur une légère reprise en 2024 (+1,4 %) et 2025 (+2,0 %). En parallèle, l'évolution de l'emploi intérieur devrait ralentir et le taux de chômage devrait augmenter. Le taux d'inflation devrait continuer à reculer graduellement, même si l'inflation sous-jacente garderait son rythme soutenu. L'augmentation de la rémunération moyenne par salarié et du coût salarial unitaire resterait élevé en 2023 et 2024. En somme, la croissance économique faible et l'impact budgétaire des mesures visant à soutenir le pouvoir d'achat des ménages et les revenus des entreprises (notamment les mesures de l'accord tripartite du 7 mars 2023, le *Solidaritéitspak 3.0*[2]) alimentent le déficit public. En conséquence, la dette publique devrait augmenter à court terme et se situer à 26,8 % du PIB en 2023, puis atteindre 28,7 % en 2024 et 29,3 % en 2025 selon les prévisions de la Commission européenne.

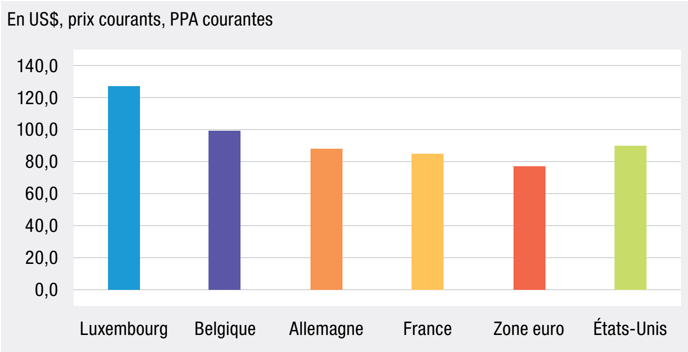
1.2.1
La productivité du travail

Le niveau et l'évolution de la productivité du travail au Luxembourg sont décrits dans ce chapitre. En outre, les résultats sont placés dans une comparaison internationale. Pour commencer, la situation est analysée au niveau agrégé de l'économie nationale. Ensuite, les différences qui existent entre les branches d'activité sont mises en avant.

1.2.1.1
La productivité du travail au niveau de l'économie nationale

Comme le CNP l'avait déjà expliqué dans ses rapports annuels précédents, deux approches se prêtent au calcul de la productivité du travail : la richesse créée, donc le PIB réel et la valeur ajoutée brute par branche d'activité, peut soit être divisée par le nombre de personnes employées, soit par le nombre d'heures travaillées. Dans les deux cas, la productivité est mesurée par une quantité de travail, et non par sa qualité. Le CNP préconise l'analyse « par heure travaillée » puisqu'elle élimine entre autres les différences entre l'emploi à plein temps et l'emploi à temps partiel et prend ainsi en compte le volume de travail réellement presté. Les analyses au niveau agrégé de l'économie nationale se basent sur les données de l'OCDE.[3]

Figure 1
Niveau de la productivité du travail, PIB par heure travaillée, 2022



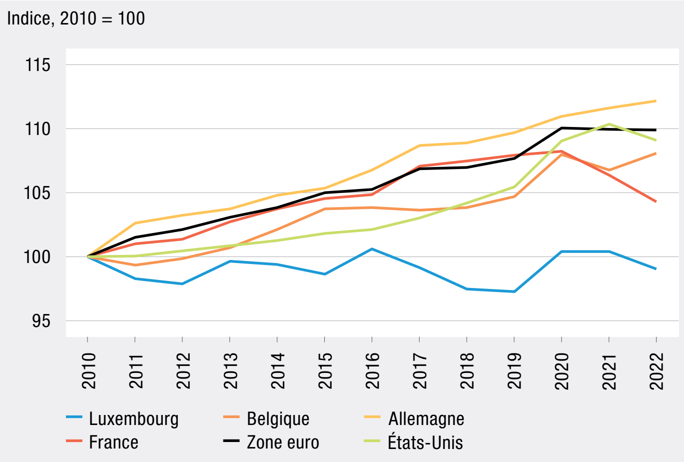
Source : OCDE

[1] European Commission, Autumn 2023 Economic Forecast, https://economy-finance.ec.europa.eu/economic-forecast-and-surveys/economic-forecasts/autumn-2023-economic-forecast-modest-recovery-ahead-after-challenging-year_en

[2] Pour plus d'informations : https://gouvernement.lu/fr/actualites/toutes_actualites/communiques/2023/03-mars/07-tripartite-signature-accord.html

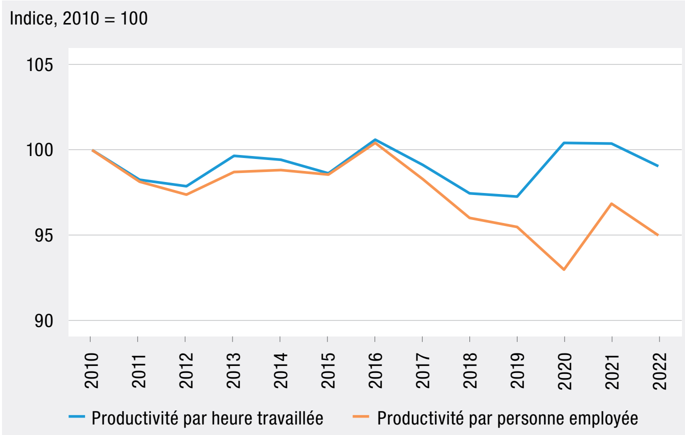
[3] Les données de l'OCDE sur la productivité du travail sont disponibles sur https://stats.oecd.org/Index.aspx?lang=fr&DataSetCode=PDB_GR.

Figure 2
Évolution de la productivité réelle du travail par heure travaillée



Source : OCDE, calculs CNP

Figure 3
Évolution de la productivité réelle du travail au Luxembourg, par heure travaillée et par personne employée



Source : OCDE, calculs CNP

Le niveau de la productivité du travail reste élevé au Luxembourg. En 2022, le PIB par heure travaillée (exprimé en dollars américains, prix courants, PPA courantes) était d'environ 127 USD au Luxembourg, qui dépasse ainsi de loin ses pays voisins, soit la Belgique (99 USD), l'Allemagne (88 USD) et la France (85 USD), tout comme la zone euro (77 USD) et les États-Unis d'Amérique (90 USD).

La performance du Luxembourg est par contre moins bonne en termes d'évolution. Depuis le début du millénaire, l'avantage du Luxembourg s'est rétréci de plus en plus. La productivité du Luxembourg a évolué en dents de scie, mais avec une très légère tendance à la baisse pour la période de 2010 à 2022 au total. L'évolution récente montre cependant que la productivité de l'économie luxembourgeoise a bien résisté face aux multiples crises des trois dernières années. La productivité réelle du travail par heure travaillée est ainsi plus élevée en 2022 qu'elle ne l'était en 2019. Contrairement au Luxembourg, les pays voisins du Grand-Duché ont évolué à la hausse sur le total de la période observée. L'Allemagne et la zone euro se distinguent par une hausse continue de leur productivité, alors que l'évolution positive de la France a été brisée en 2021 et 2022 par les séquelles des crises récentes. La productivité de la Belgique a évolué à un rythme inférieur à celui de la zone euro jusqu'en 2019, mais a bondi en 2020 et s'est stabilisée à ce niveau ensuite. La productivité du travail des États-Unis a évolué lentement mais continuellement entre 2010 et 2019 ; l'évolution a ensuite accéléré en 2020 et 2021, puis elle s'est légèrement redressée en 2022.

L'évolution médiocre de la productivité du travail au Luxembourg est encore plus inquiétante si on analyse la richesse créée par personne employée. En effet, on peut observer que depuis 2017 l'évolution de la productivité par heure travaillée et celle par personne employée divergent de plus en plus au Luxembourg.

L'écart entre les deux indicateurs était le plus important en 2020, année marquée par le pic de la pandémie de COVID-19 et par des mesures exceptionnelles du gouvernement luxembourgeois en faveur du maintien de l'emploi. Bien que l'écart se soit rétréci depuis, il reste que la productivité par personne employée est à la traîne. Elle se trouve actuellement en dessous de son niveau pré-crise de 2019 et a en tout baissé de 5 % depuis 2010. L'évolution divergente des deux indicateurs est notamment due au fait que la moyenne des heures travaillées par employé et par année affiche une tendance à la baisse au cours de la période observée. Plusieurs facteurs peuvent expliquer cette évolution : le recours accru au travail à temps partiel, l'extension des congés légaux et spéciaux ou encore la hausse du taux d'absentéisme[4] observée au Luxembourg au cours des dernières années. Cette réduction du temps de travail moyen pèse principalement sur la productivité par personne employée et provoque en outre un besoin supplémentaire d'emplois et, par conséquent, un besoin accru de logements, d'infrastructures, de mobilité, etc.

La divergence entre la mesure de la productivité par heure travaillée et par personne employée ne vaut pas seulement pour le Luxembourg, mais peut être observée également dans ses pays voisins et au niveau de l'UE dans son ensemble, où l'écart entre les deux indicateurs est pourtant moins prononcé. En tout, il apparaît que l'évolution de la productivité au Luxembourg est défavorable en comparaison internationale, indépendamment de l'indicateur pris pour base.

En lien direct avec la productivité, force est de constater que le coût salarial unitaire nominal, donc le coût du travail corrigé de la productivité, croît plus vite au Luxembourg que dans ses pays voisins, la zone euro ou encore l'UE dans son ensemble, entraînant ainsi une perte de la compétitivité-coût du Grand-Duché.[5]

[4] Inspection générale de la sécurité sociale, Aperçu N° 25 – L'absentéisme pour cause de maladie en 2022, https://igss.gouvernement.lu/fr/publications/apercus-et-cahiers/apercus/202310no25.html

[5] Des données d'Eurostat sur la productivité du travail et le coût salarial unitaire sont disponibles sur https://ec.europa.eu/eurostat/web/products-datasets/-/nama_10_lp_ulc

1.2.1.2

La productivité du travail par secteur

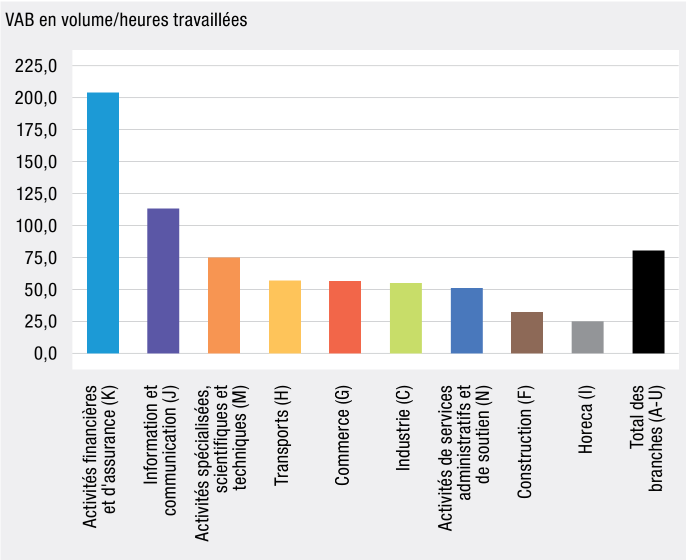
Derrière l'évolution de la productivité du travail au niveau agrégé de l'économie nationale se cachent des disparités sectorielles importantes qu'il convient d'étudier plus en détail. Les analyses au niveau sectoriel se basent sur les données de la comptabilité nationale du Luxembourg compilées par le STATEC. Pour les besoins de cette analyse, l'économie nationale est divisée en 21 sections identifiées par un code alphabétique, soit le premier niveau de la structure hiérarchique de la nomenclature statistique NACE Rév. 2. La productivité du travail est calculée en divisant pour chaque branche la valeur ajoutée brute aux prix de base (en volume) par le nombre d'heures travaillées au total. Les taux de croissance annuels sont calculés par une moyenne géométrique pour différentes périodes.[6]

La branche des activités financières et d'assurance (K) affichait de loin le niveau le plus élevé en termes de productivité du travail en 2022 ; son niveau était environ 2,5 fois plus élevé que celui du total des branches. Parmi les branches de l'économie marchande retenues pour la présente analyse descriptive suivent par ordre décroissant l'information et la communication (J), les activités spécialisées, scientifiques et techniques (M), les transports et l'entreposage (H), le commerce (G), l'industrie manufacturière (C), les activités de services administratifs et de soutien (N), la construction (F) et finalement l'hébergement et la restauration (I).

L'évolution de la productivité du travail des différents secteurs diffère aussi fortement. De manière générale, les données montrent des variations annuelles importantes pour tous les secteurs, tant à la hausse qu'à la baisse. Toutes branches confondues (ensemble des sections A-U), la productivité du travail de l'économie luxembourgeoise a très légèrement baissé sur le total de la période observée. De 2010 à 2022, la valeur ajoutée brute a augmenté d'environ 2,4 % par année, alors que la croissance des heures travaillées était d'environ 2,5 % ; il en résulte une quasi-stagnation de la productivité du travail sur les douze dernières années. Au cours des trois dernières années, la tendance de la productivité du travail s'est reprise un peu malgré les crises successives. Sur le total de la période de 2020 à 2022, la valeur ajoutée brute a augmenté d'environ 2,5 % en moyenne annuelle, alors que les heures travaillées ont évolué de seulement 1,9 %, menant ainsi à une hausse annuelle moyenne de la productivité du travail de 0,6 % pour l'ensemble de l'économie nationale.

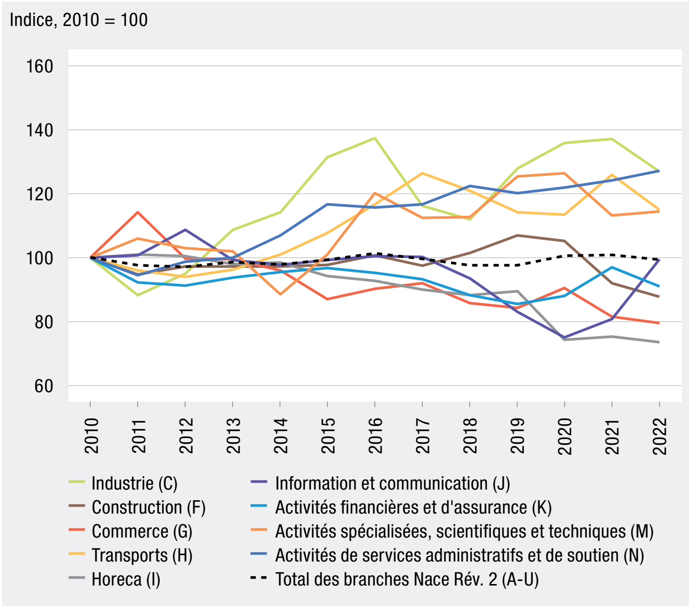
Parmi les principales branches de l'économie marchande, ce sont les services administratifs, l'industrie manufacturière, les transports et les activités spécialisées qui ont connu une hausse de leur productivité du travail depuis 2010. La branche de l'information et de la communication vient de retrouver son niveau d'il y a douze ans, alors que les activités financières et d'assurance, la construction, le commerce et le secteur de l'hébergement et de la restauration ont perdu en productivité sur le total de la période 2010-2022.

Figure 4
Niveau de la productivité du travail au Luxembourg, 2022, branches sélectionnées



Source : STATEC, calculs CNP

Figure 5
Évolution de la productivité du travail au Luxembourg, branches sélectionnées



Source : STATEC, calculs CNP

[6] Les données des comptes nationaux sont disponibles dans la rubrique « Économie totale et prix » sur https://statistiques.public.lu/fr/donnees/indicateurs-court-terme.html. Le tableau E2305 renseigne sur la valeur ajoutée brute (B1) aux prix de base par branche (NACE Rév. 2) (en volume aux prix de l'année précédente chaînés ; année de référence = 2015) ; le tableau E2312 renseigne sur les heures travaillées total par branche (NACE Rév. 2).

Plus en détail, les activités de services administratifs et de soutien (N) ont évolué à la hausse entre 2010 et 2022, tant en termes de valeur ajoutée (5,8 % en moyenne par année) qu'en termes d'heures travaillées (3,7 %), avec à la clé une hausse annuelle de la productivité d'environ 2,0 %. L'évolution a un peu ralenti depuis 2020, mais les taux de croissance moyens sont restés positifs pour la valeur ajoutée, les heures travaillées et la productivité au cours des trois dernières années.

L'industrie manufacturière (C) s'est également bien développée sur le total de la période observée. La croissance annuelle moyenne de la productivité (2,0 %) depuis 2010 a résulté d'une hausse de la valeur ajoutée brute (1,8 %) et d'une quasi-stagnation des heures travaillées (-0,2 %). Plus récemment, entre 2020 et 2022, la tendance s'est cependant inversée. La valeur ajoutée brute (-2,0 %), les heures travaillées (-1,7 %) et la productivité (-0,2 %) ont baissé en moyenne annuelle depuis 2019.

La branche des transports et d'entreposage (H) a également bien évolué entre 2010 et 2022. La hausse annuelle de la productivité du travail (1,2 %) s'explique par une croissance plus élevée de la valeur ajoutée brute (2,4 %) que la croissance des heures travaillées (1,3 %). L'évolution a un peu ralenti au cours des trois dernières années, mais les taux de croissance sont restés positifs en moyenne pour les trois éléments.

La branche des activités spécialisées, scientifiques et techniques (M) a aussi connu une hausse de la productivité du travail sur le total des douze dernières années. En moyenne annuelle, la valeur ajoutée (6,0 %) a augmenté plus vite que les heures travaillées (4,9 %) entre 2010 et 2022. Le développement du secteur a toutefois été freiné par les crises récentes. Entre 2020 et 2022, la croissance de la valeur ajoutée brute (0,8 %) était bien inférieure à celle des heures travaillées (3,9 %), équivalant à une baisse de la productivité (-3,0 %).

La branche de l'information et de la communication (J) a connu une stagnation de sa productivité sur le travail sur le total de la période observée du fait que la valeur ajoutée (3,4 %) et les heures travaillées (3,5 %) ont évolué à un rythme similaire en moyenne annuelle entre 2010 et 2022. Derrière cette stagnation se cachent cependant des évolutions divergentes au cours des années. En effet, la productivité a peu fluctué entre 2010 et 2017, puis elle est tombée rapidement jusqu'en 2020 et s'est bien reprise ensuite. Il est toutefois à noter que les taux de croissance de la valeur ajoutée et des heures travaillées sont restés positifs sur l'ensemble de la période.

Les activités financières et d'assurance (K), branche dominante de l'économie nationale, ont connu une baisse de leur productivité sur le total de la période observée (-0,8 % en moyenne annuelle). Entre 2010 et 2019, la valeur ajoutée brute a peu évolué (0,3 %), alors que les heures travaillées ont augmenté de 2,1 % en moyenne annuelle, signifiant une baisse de la productivité (-1,7 %) au cours de cette période. La situation s'est ensuite inversée entre 2020 et 2022, avec une hausse de la valeur ajoutée d'environ 4,6 % par année contre une hausse de 2,4 % pour les heures travaillées et, en conséquence, une hausse de la productivité du travail de 2,1 % en moyenne annuelle pour les trois dernières années.

Déjà à un niveau relativement bas, la productivité du travail a encore baissé dans le secteur de la construction (F) sur le total de la période observée. Entre 2010 et 2019, la valeur ajoutée a évolué plus fortement en moyenne que les heures travaillées, signifiant une légère hausse de la productivité. La situation s'est cependant détériorée pendant les années de crise. La valeur ajoutée du secteur est en baisse continue depuis 2020, malgré une hausse des heures travaillées en 2021 et 2022. Sur le total des trois dernières années, la construction a ainsi connu une baisse conséquente de sa productivité, avec un taux de -6,4 % en moyenne annuelle sur la période 2020-2022.

Entre 2010 et 2022, le commerce (G) a également connu une tendance à la baisse de sa productivité du travail (-1,9 %) en raison d'une baisse de sa valeur ajoutée (-0,6 %) et en même temps une hausse des heures travaillées (1,3 %). La situation du secteur s'est encore détériorée davantage au cours des trois dernières années, avec une baisse de sa valeur ajoutée (-1,7 %) et une quasi-stagnation des heures travaillées (0,3 %) pendant la période 2020-2022.

Le secteur de l'hébergement et de la restauration (I) a connu un déclin de sa productivité tout au long de la période observée. Entre 2010 et 2019, la valeur ajoutée a évolué moins vite que les heures travaillées, mais les taux de croissance étaient positifs pour les deux éléments. La crise sanitaire liée au COVID-19 a ensuite frappé de plein fouet le secteur de l'Horeca en 2020. Depuis, le secteur n'a pas encore réussi à retrouver son niveau d'activité pré-crise. Pour les années 2020 à 2022, la valeur ajoutée a baissé de -7,0 % et les heures travaillées de -0,7 % en moyenne annuelle, signifiant une baisse supplémentaire de sa productivité (-6,3 %).

Tableau 1
Croissance annuelle de la productivité du travail au Luxembourg, périodes sélectionnées, par branche (en %)

Productivité du travail	**2010-2014**	**2015-2019**	**2020-2022**	**Total 2010-2022**
Agriculture, sylviculture et pêche (A)	-2,7 %	0,0 %	0,0 %	-0,9 %
Industries extractives (B)	-1,6 %	-3,6 %	-3,1 %	-2,8 %
Industrie manufacturière (C)	3,3 %	2,3 %	-0,2 %	2,0 %
Production et distribution d'électricité, de gaz, de vapeur et d'air conditionné (D)	8,7 %	5,3 %	-23,7 %	-1,8 %
Production et distribution d'eau ; assainissement, gestion des déchets et dépollution (E)	-3,6 %	-2,1 %	-0,3 %	-2,1 %
Construction (F)	-0,7 %	1,9 %	-6,4 %	-1,1 %
Commerce ; réparation d'automobiles et de motocycles (G)	-1,0 %	-2,5 %	-2,0 %	-1,9 %
Transports et entreposage (H)	0,3 %	2,5 %	0,2 %	1,2 %
Hébergement et restauration (I)	-0,4 %	-1,9 %	-6,3 %	-2,5 %
Information et communication (J)	-0,6 %	-3,2 %	6,2 %	0,0 %
Activités financières et d'assurance (K)	-1,2 %	-2,2 %	2,1 %	-0,8 %
Activités immobilières (L)	-0,7 %	-3,5 %	-0,7 %	-1,9 %
Activités spécialisées, scientifiques et techniques (M)	-3,1 %	7,3 %	-3,0 %	1,1 %
Activités de services administratifs et de soutien (N)	1,7 %	2,3 %	1,9 %	2,0 %
Administration publique (O)	0,8 %	0,4 %	-0,3 %	0,4 %
Enseignement (P)	-0,4 %	-1,4 %	0,3 %	-0,6 %
Santé humaine et action sociale (Q)	-3,1 %	-0,1 %	5,2 %	0,2 %
Arts, spectacles et activités récréatives (R)	-2,7 %	-0,7 %	-1,9 %	-1,7 %
Autres activités de services (S)	-1,2 %	-0,8 %	0,5 %	-0,6 %
Activités des ménages en tant qu'employeurs ; activités indifférenciées des ménages en tant que producteurs de biens et services pour usage propre (T)	0,0 %	0,0 %	-3,1 %	-0,8 %
Activités extraterritoriales (U)	n/a	n/a	n/a	n/a
Total des branches (A-U)	*-0,5 %*	*0,0 %*	*0,6 %*	*-0,1 %*

Source : STATEC, calculs CNP

Encadré 1
La productivité du secteur public

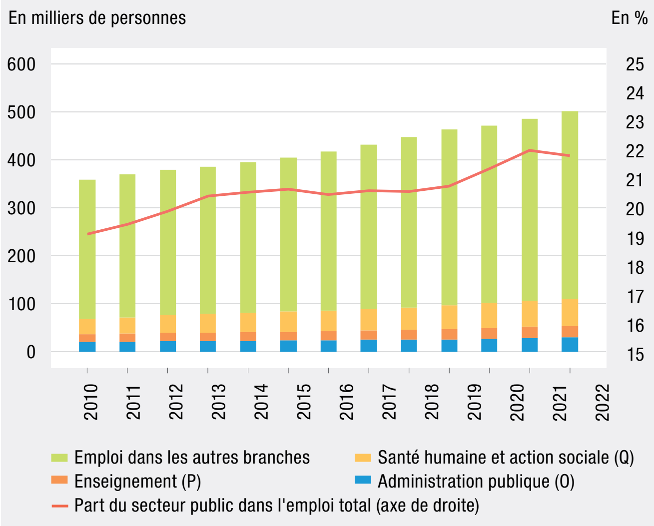
L'analyse détaillée de la productivité du travail par secteur présentée dans ce chapitre se limite aux branches principales de l'économie marchande. L'administration publique et les branches à dominante non marchande sont donc exclues de l'analyse. Le secteur public représente cependant une partie considérable et croissante de l'économie nationale et a ainsi un impact significatif sur la productivité globale de l'économie luxembourgeoise. Ensemble, l'administration publique (section O de la NACE Rév.2), l'enseignement (P) et la santé humaine et l'action sociale (Q) ont représenté 21,8 % de l'emploi total et 17,3 % de la valeur ajoutée brute en 2022 au Luxembourg.[7] Vu son importance, il est indiqué d'analyser également la productivité du secteur public.

Mesurer la productivité du secteur public est un exercice compliqué, la principale difficulté étant que la production du secteur public n'a en général pas de valeur de marché ; les services non marchands sont fournis gratuitement ou à des prix qui ne sont pas économiquement significatifs. Ceci tient notamment aux objectifs du secteur public qui sont fondamentalement différents de ceux du secteur privé. Le secteur public n'a pas pour vocation de générer des bénéfices et de les maximiser, mais de satisfaire des besoins sociaux de manière équitable et démocratique en mettant à disposition des biens communs et publics (p.ex. infrastructures) et en rendant des services publics (dont entre autres la santé, l'éducation, les services aux collectivités et autres services gouvernementaux). En outre, les objectifs de l'action publique sont moins de nature quantitative, mais plutôt de nature qualitative (efficacité des services publics), ce qui rend difficile la mesure de la productivité du secteur public par des outils usuels comme le ratio input/output utilisé pour évaluer le secteur marchand. Nonobstant ces difficultés de mesure, améliorer la productivité et l'efficience du secteur non marchand est possible et doit être un objectif.

Il existe une panoplie de *benchmarks* internationaux qui comparent l'efficacité et l'efficience du secteur public dans différents pays, mais les indicateurs utilisés négligent dans la plupart des cas la qualité des services et une comparaison internationale reste difficile dû à un manque de méthodes standardisées. À titre d'exemple, différents *benchmarks* sont répertoriés ci-dessous :

- La Banque mondiale publie les *Worldwide Governance Indicators*. Ici, le Luxembourg se classe 6e en 2022 pour l'indicateur *Government effectiveness* et 5e pour la *Regulatory quality*. [8]

Figure 6
Emploi dans les différentes branches de l'économie (en milliers de personnes, axe de gauche) et part du secteur public (somme des sections O, P, Q de la NACE Rév. 2) dans l'emploi total (en %, axe de droite)



Source : STATEC, calculs CNP

- La Bertelsmann Stiftung publie les *Sustainable Governance Indicators* parmi lesquels figure p.ex. la catégorie *Executive capacity* qui synthétise la capacité du secteur public d'agir dans le but d'une gouvernance soutenable à long terme et où le Luxembourg occupe la 16e position sur 41 pays analysés en 2022.[9]

- Le European Institute of Public Administration a publié récemment une étude appelée *International Public Sector Performance Benchmarking Study* qui compare les 27 États membres de l'UE et 8 autres pays. Le Luxembourg se classe 6e en matière de *Government effectiveness* et 2e du *Public sector performance indicator*.[10]

- La Commission européenne publie régulièrement le *eGovernment Benchmark* qui examine la numérisation des services publics en Europe. Dans l'édition 2023, le Luxembourg se en classe 3e position et est considéré comme pays performant en termes de maturité de l'e-gouvernement.[11]

Le Conseil national de la productivité envisage une analyse plus approfondie de la productivité du secteur public au Luxembourg. Pour démarrer les travaux, le CNP a contacté l'Observatoire de la Fonction publique et le ministère de la Digitalisation en vue d'élaborer des pistes potentielles à suivre. Les résultats de ces travaux seront présentés dans un prochain rapport annuel du CNP.

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[7] Les données correspondantes des comptes nationaux sont compilées par le STATEC et disponibles dans la rubrique « Économie totale et prix » sur https://statistiques.public.lu/fr/donnees/indicateurs-court-terme.html. Le tableau E2304 renseigne sur la valeur ajoutée brute aux prix de base par branche (à prix courants) ; le tableau E2309 renseigne sur l'emploi total par branche.

[8] Pour plus de détails : https://www.govindicators.org/interactive-data-access

[9] Pour plus de détails : https://www.sgi-network.org/2022/Luxembourg/Executive_Summary

[10] Pour plus de détails : https://www.eipa.eu/services/research-and-performance-analysis/

[11] Pour plus de détails : https://digital-strategy.ec.europa.eu/en/library/egovernment-benchmark-2023

1.2.2
La contribution des facteurs à l'évolution de la productivité

Après avoir décrit la productivité du travail au Luxembourg, il est indiqué de regarder plus en détail les différents facteurs de production et leur contribution à l'évolution de la productivité et du PIB. Les statistiques de l'OCDE, agrégées au niveau de l'économie nationale, se prêtent en la matière et servent de base pour les analyses qui suivent.[12] Il est cependant à noter que la dernière mise à jour des données date de décembre 2022 et ne tient pas compte des données actualisées des comptes nationaux et diffère donc des données utilisées pour l'analyse macroéconomique de la productivité du travail ci-dessus (chapitre 1.2.1 du présent rapport). En plus, dans ces statistiques de l'OCDE, il ne s'agit pas toujours de données observées, mais de données calculées ou estimées, notamment en ce qui concerne les services du capital et la productivité multifactorielle. En conséquence, le CNP appelle à la prudence dans l'interprétation des résultats. Malgré les limites méthodologiques, les analyses peuvent fournir un aperçu complémentaire de l'évolution de la productivité de l'économie.

Le travail n'est bien sûr pas le seul intrant dans la production. S'y ajoutent les capitaux engagés, notamment le capital technique (installations, machines, outillages, etc.) et le capital intangible, comme le savoir-faire accumulé des entreprises, les compétences de la main-d'œuvre ou encore les outils numériques. Pour les besoins de l'analyse statistique, le facteur capital est couramment divisé en capital TIC (matériel informatique, équipements de télécommunication, logiciels et bases de données, etc.) et capital non-TIC (autres machines et équipements, matériel de transport, construction non résidentielle, recherche et développement, droits de propriété intellectuelle, etc.).

En dépit de la croissance constante des heures travaillées, le regard sur la croissance des facteurs montre une intensification en capital de l'économie luxembourgeoise. En effet, les services du capital, c'est-à-dire les services productifs tirés du stock cumulé des investissements réalisés, ont augmenté plus vite que le facteur travail entre 2010 et 2022. Plus en détail, c'est surtout la montée en puissance du capital TIC qui est frappante.

Tableau 2
Luxembourg, évolution des facteurs de production (Indice, 2010 = 100)

	2010	2015	2020	2021	2022
Heures travaillées totales	100,0	112,8	121,6	130,5	135,6
Total des services du capital	100,0	124,7	144,5	149,2	152,5
Capital TIC	100,0	148,6	232,8	251,3	266,2
Capital non-TIC	100,0	122,1	136,5	139,9	142,2

Source : OCDE, calculs CNP

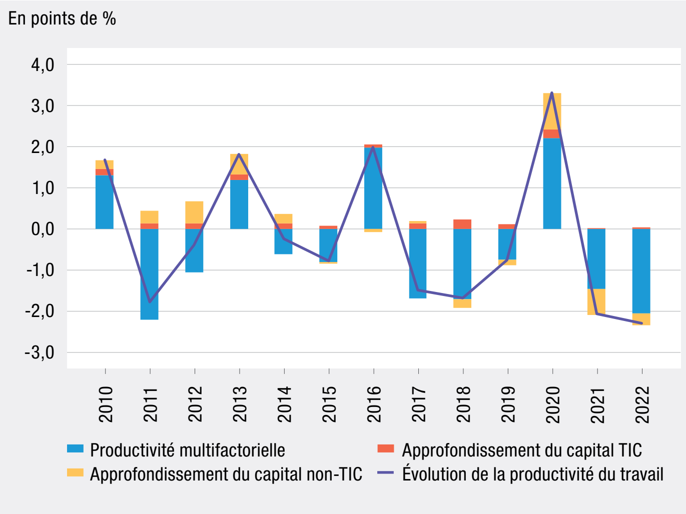
À côté de la productivité du travail et du capital, la productivité multifactorielle (ou productivité globale des facteurs, PGF) est une autre mesure usuelle de la productivité. La PGF rend compte de l'efficience globale avec laquelle les facteurs travail et capital sont conjointement utilisés dans le processus de production. La PGF est en fait un résidu obtenu en défalquant la contribution – pondérée et en volume – des deux autres facteurs de production que sont le capital et le travail. La PGF permet donc de représenter la variation de la productivité qui ne peut pas être expliquée par l'évolution des facteurs travail et capital. Comparée à ses pays voisins, l'évolution de la productivité globale des facteurs est relativement faible au Luxembourg et connaît même une tendance à la baisse depuis la crise financière de 2008/2009. En moyenne, la PGF a baissé de -0,44 % par année au Luxembourg pendant la période de 2010 à 2022, contre une quasi-stagnation en France (+0,03 %) et des hausses plus marquées en Belgique (+0,20 %), aux États-Unis (+0,46 %) et surtout en Allemagne (+0,82 %).

Pour les besoins d'analyse, le capital et la PGF peuvent être interprétés comme facteurs d'influence qui alimentent la productivité du travail. Dans cette approche, il est intéressant de voir la contribution de chacun de ces facteurs à l'évolution de la productivité du travail.

D'après les statistiques de l'OCDE, il apparaît que la productivité multifactorielle est le principal contributeur à l'évolution de la productivité du travail au Luxembourg, tant à la hausse qu'à la baisse. En moyenne, la contribution de la PGF à la productivité du travail est négative au cours de la période observée. L'impact de l'approfondissement du capital est plus faible. En moyenne, les investissements réalisés ont un impact positif sur l'évolution annuelle de la productivité du travail au Luxembourg, tant pour ce qui est du capital TIC que du capital non-TIC. Il est à noter que tout au long de la période observée, l'approfondissement du capital TIC a apporté une contribution positive à la productivité du travail, alors que la contribution de l'approfondissement du capital non-TIC est parfois positive et parfois négative, mais les effets positifs prédominent au total. Ces constats ne valent d'ailleurs pas seulement pour le Luxembourg. Des effets similaires sont observés dans beaucoup d'économies en Europe et à travers le monde.

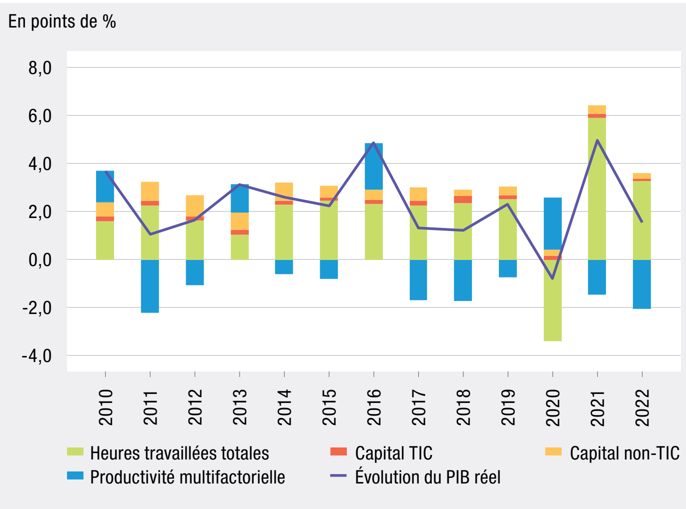
[12] Les données de l'OCDE sur la productivité et la contribution des facteurs de production sont disponibles sur https://stats.oecd.org/Index.aspx?lang=fr&DataSetCode=PDB_GR.

Figure 7
Luxembourg, contribution des facteurs à la croissance annuelle de la productivité du travail



Note de lecture : La croissance (baisse) de la productivité du travail reflète un niveau plus (moins) élevé de valeur ajoutée créée pour chaque heure travaillée. Une croissance ne peut être atteinte que si plus de capital est utilisé dans la production ou en cas d'amélioration de l'efficacité globale avec laquelle le travail et le capital sont utilisés ensemble. Pour cette analyse, l'évolution de la productivité du travail est ainsi décomposée en contribution de l'approfondissement du capital et en croissance de la productivité multifactorielle. L'approfondissement du capital est basé sur le concept de l'intensité du capital, soit le ratio des services du capital par unité d'heure travaillée. L'approfondissement du capital est alors défini comme le changement en intensité capitalistique, c'est-à-dire l'évolution de ce ratio. La productivité multifactorielle, qui évalue l'efficience globale, est un facteur résiduel qui mesure la part de l'évolution de la productivité du travail qui ne peut pas être expliquée par la croissance du facteur capital.
Source : OCDE, calculs CNP

Figure 8
Luxembourg, contribution des facteurs à la croissance annuelle du PIB



Source : OCDE, calculs CNP

1.2.3
La productivité et l'évolution du PIB

Sur base des statistiques de l'OCDE, force est de constater que la croissance de l'économie luxembourgeoise n'est pas soutenue par des gains de productivité. En effet, c'est principalement l'augmentation du volume de travail qui porte la croissance du PIB. Sur les 2,29 % de croissance annuelle moyenne du PIB réel entre 2010 et 2022, la croissance des heures travaillées a contribué à elle seule à hauteur de 2,03 points de pourcentage (pp). La croissance du capital a également alimenté l'évolution du PIB, mais son apport est beaucoup moindre que celui du facteur travail. En moyenne, la contribution annuelle du capital TIC était de +0,17 pp et celle du capital non-TIC de +0,52 pp. L'évolution de la productivité multifactorielle a par contre pesé sur l'évolution du PIB (-0,44 pp par année en moyenne).

Ce développement semble difficilement soutenable à terme et les effets de cette croissance par l'emploi se font déjà ressentir aujourd'hui. Parmi les effets indésirables, on retrouve par exemple la pression sur le marché du logement, l'impact sur la mobilité ou encore la pénurie d'une main-d'œuvre qualifiée. La transition vers une croissance basée davantage sur les gains de productivité semble donc nécessaire. Ceci ne signifie pas que la croissance de l'emploi est à rejeter d'office, mais qu'un meilleur équilibre entre les différents facteurs qui contribuent à la croissance économique est à viser.

1.2.4
La productivité des ressources et de l'énergie

Dans une optique de développement durable, cette partie retrace l'évolution de la productivité des ressources et celle de l'énergie au cours des douze dernières années, de 2010 à 2021, les données définitives pour l'année 2022 n'étant pas encore disponibles au moment de la rédaction du rapport. L'analyse descriptive vise le long terme afin de déceler des changements structurels éventuels. Le Conseil national de la productivité s'engage à répéter régulièrement cet exercice d'analyse afin de suivre les efforts du Luxembourg dans la transition écologique de son économie.

1.2.4.1
La productivité des ressources

La productivité des ressources, soit le produit intérieur brut (PIB) divisé par la consommation intérieure de matières[13] (CIM), est un des indicateurs utilisés par Eurostat pour suivre le progrès de l'Union européenne et de ses États membres vers la réalisation des objectifs de développement durable (ODD) établis par les Nations Unies. La productivité des ressources fait partie des indicateurs de l'ODD 12 qui vise à établir des modes de consommation et de production durables. L'indicateur permet de mesurer le découplage des impacts environnementaux de la croissance économique.[14]

[13] La consommation intérieure de matières (CIM) désigne la consommation totale de matières générée par la demande intérieure dans l'économie et exclut donc la consommation liée au marché à l'exportation. La CIM correspond donc à l'extraction intérieure, majorée des importations et diminuée des exportations de matières.

[14] Les données d'Eurostat sur la productivité des ressources sont disponibles sur https://ec.europa.eu/eurostat/web/products-datasets/-/env_ac_rp. Les données de la consommation intérieure de matières se basent sur les comptes de flux de matières disponibles sur https://ec.europa.eu/eurostat/web/products-datasets/-/env_ac_mfa.

Comparé aux autres États membres et à l'Union européenne dans son ensemble, le niveau de la productivité des ressources reste élevé au Luxembourg. Exprimé en standard de pouvoir d'achat (SPA) par kilogramme, seuls les Pays-Bas et l'Italie devancent le Luxembourg en 2021 pour cet indicateur. Par contre, la performance du pays est moins bonne en termes d'évolution. Il apparaît que le Luxembourg n'a pas réussi à découpler sa consommation intérieure de matières de sa croissance économique au cours de la dernière décennie. Comparé à ses pays voisins et à l'UE dans son ensemble, le Grand-Duché est le seul à enregistrer une détérioration de sa productivité des ressources. En effet, la productivité des ressources a baissé de -5,5 % au Luxembourg sur le total de la période de 2010 à 2021, alors qu'elle a augmenté en Belgique (+28,3 %), en France (+10,0 %), en Allemagne (+20,0 %) et dans l'UE-27 dans son ensemble (+13,3 %).

Le regard sur la consommation intérieure de matières du Luxembourg montre une tendance à la hausse entre 2010 et 2021, passant de 11 393 à 15 777 mille tonnes. Ainsi, la CIM a augmenté de 38,5 % au total en douze ans. Plus en détail, c'est la catégorie des minerais non métalliques et ici la classe du sable et gravier qui a connu la hausse la plus importante. Après de légères hausses entre 2010 et 2014, la consommation de minerais non métalliques a bondi en 2015, puis elle a ralenti un peu jusqu'en 2020, mais elle est repartie à la hausse en 2021. La consommation de matières énergétiques fossiles a varié plus ou moins fortement d'année en année, tantôt à la hausse, tantôt à la baisse. La tendance reste cependant relativement stable au total et aucun changement structurel ne peut être observé dans la consommation de matières énergétiques fossiles au cours de la période de 2010 à 2021. La catégorie de la biomasse a connu une hausse importante récemment, notamment à cause de la consommation de bois qui a quasi doublé en 2021 par rapport à l'année précédente. La consommation de minerais métalliques (minerais bruts) est restée stable en gros au cours de la période observée, signifiant que sa part relative a diminué au cours des douze dernières années.

La catégorie des autres produits ainsi que les déchets pour traitement et élimination définitifs restent marginaux dans la consommation intérieure de matières du Luxembourg.

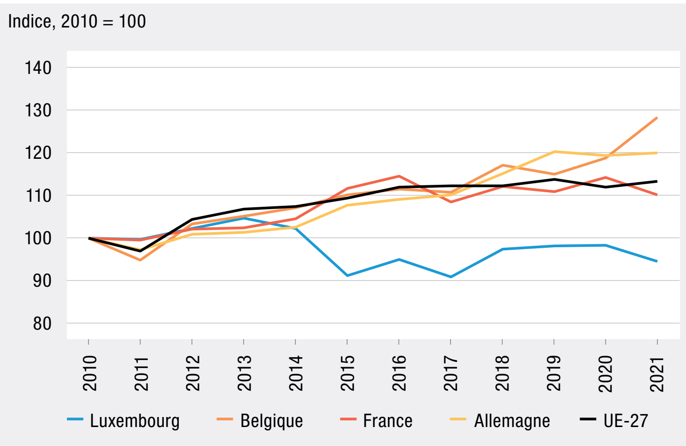
Au-delà des matières, le foncier est une autre ressource primordiale qu'il s'agit de considérer dans les objectifs de développement durable, notamment en vue de la protection de la nature et de la biodiversité. Du fait que le Luxembourg se caractérise par une artificialisation relativement élevée des sols, le CNP suggère d'effectuer une analyse de la productivité du foncier afin d'étudier plus en détail l'artificialisation et l'utilisation du sol.

1.2.4.2
La productivité de l'énergie

La productivité de l'énergie est également un des indicateurs utilisés par Eurostat pour suivre le progrès de l'UE et de ses États membres vers la réalisation des objectifs de développement durable établis par les Nations Unies. L'indicateur fait partie des indicateurs de l'ODD 7 qui vise à garantir l'accès de tous à des services énergétiques modernes, à améliorer l'efficacité énergétique et à accroître la part d'énergie renouvelable. L'indicateur mesure la quantité de production économique produite par unité d'énergie brute disponible (en milliers de tonnes équivalent pétrole).[15]

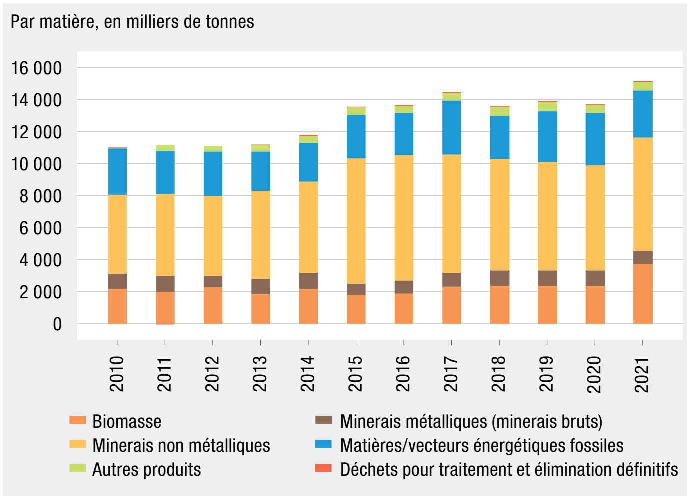
Comparé aux autres États membres et à l'UE dans son ensemble, le niveau de la productivité de l'énergie reste élevé au Luxembourg. Exprimé en standard de pouvoir d'achat (SPA) par kilogramme d'équivalent pétrole, seuls l'Irlande, le Danemark et la Roumanie devancent le Luxembourg en 2021 pour cet indicateur. La performance du pays est également bonne en termes d'évolution. Tout comme les autres États membres de l'UE, le Luxembourg a réussi, au moins en partie et au niveau agrégé de l'économie nationale, à découpler sa consommation d'énergie de sa croissance économique.

Figure 9
Évolution de la productivité des ressources



Source : Eurostat, calculs CNP

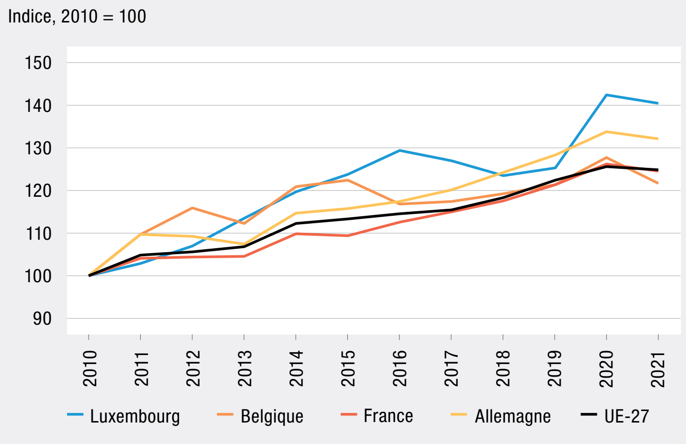
Figure 10
Évolution de la CIM au Luxembourg



Source : Eurostat, calculs CNP

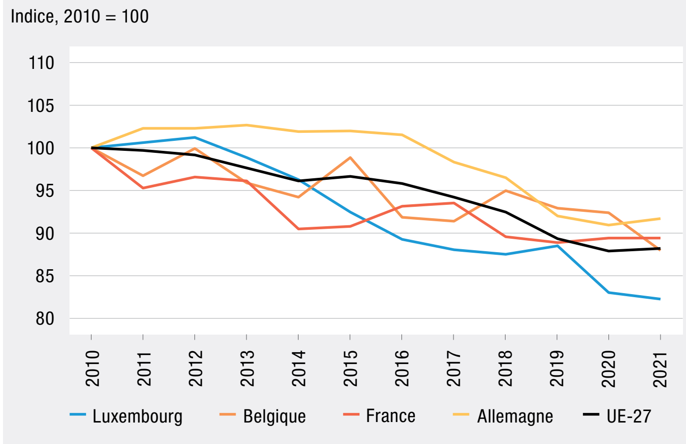
[15] Les données d'Eurostat sur la productivité de l'énergie sont disponibles sur https://ec.europa.eu/eurostat/web/products-datasets/-/sdg_07_30.

Figure 11
Évolution de la productivité de l'énergie



Source : Eurostat, calculs CNP

Figure 12
Évolution de l'intensité d'émissions de gaz à effet de serre par consommation d'énergie



Sources : AEE et Eurostat, calculs CNP

En comparaison avec ses pays voisins et l'UE dans son ensemble, le Grand-Duché s'illustre comme bon élève. En effet, le Luxembourg (+40,4 % au total) a connu la hausse la plus importante de sa productivité de l'énergie au cours des douze dernières années. Les hausses enregistrées entre 2010 et 2021 en Allemagne (+32,0 %), en France (+24,5 %), en Belgique (+21,6 %) et pour l'UE dans son ensemble (+24,9 %) étaient moins prononcées.

En parallèle, le Luxembourg a réussi à réduire ses émissions de gaz à effet de serre liées à la consommation intérieure brute d'énergie. Alors que l'intensité des émissions avait encore augmenté du début du millénaire jusqu'en 2010, elle a fortement baissé depuis. En effet, au cours des douze dernières années, l'intensité des émissions a diminué plus fortement au Luxembourg (-17,7 % au total) que dans l'UE-27 dans son ensemble (-11,7 %).[16] La bonne évolution de l'intensité des émissions de l'économie luxembourgeoise est également confirmée par les données de la Banque mondiale[17] et par les données de l'OCDE sur les émissions de gaz à effet de serre et de polluants de l'air.[18] Il reste cependant le bémol que la part des énergies renouvelables dans la consommation finale brute d'énergie du Luxembourg est parmi les plus faibles en Europe avec un taux de 11,7 % en 2021, contre 21,8 % pour l'UE-27 dans son ensemble.[19] En conséquence, le Luxembourg accuse toujours une intensité élevée d'émissions de gaz à effet de serre, même si le pays affiche une tendance à la baisse sur le long terme. À côté de l'efficacité énergétique, le développement des énergies renouvelables est crucial en vue d'atteindre l'objectif de neutralité carbone à l'horizon 2050.

Du fait que le potentiel de production national est limité en raison de la petite taille du territoire, la coopération au niveau européen s'impose dans la production d'électricité renouvelable. La consommation de carburants routiers est un autre domaine d'action pour réduire les émissions de gaz à effet de serre. Comparé à ses pays voisins, le Luxembourg accuse un niveau très élevé de consommation de carburants par habitant dû au faible niveau de prix qui favorise non seulement le « tourisme à la pompe », mais qui contribue également à une surconsommation totale. Dans son examen environnemental du Luxembourg en 2020, l'OCDE recommande ainsi que « les taxes sur les carburants routiers augmentent davantage pour les rapprocher de ceux des pays voisins et que le taux d'accise sur le diesel rejoigne celui de l'essence. Cela apporterait des bénéfices en termes d'émissions de GES, de pollution atmosphérique et d'encombrement routier. Les pertes de recettes entraînées par une moindre consommation de carburants pourraient être compensées par un recours accru à la taxation environnementale dans le cadre d'une réforme fiscale plus large ».[20]

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16 Les données sur les émissions de gaz à effet de serre par secteur source sont disponibles sur https://ec.europa.eu/eurostat/web/products-datasets/-/env_air_gge.

17 Les données de la Banque mondiale sur les émissions de CO_2 par unité de PIB sont disponibles sur https://data.worldbank.org/indicator/EN.ATM.CO2E.KD.GD.

18 Les données de l'OCDE sur les émissions de GES sont disponibles sur https://data.oecd.org/air/air-and-ghg-emissions.htm.

19 Les données d'Eurostat sur la part des énergies renouvelables dans la consommation finale brute d'énergie sont disponibles sur https://ec.europa.eu/eurostat/web/products-datasets/-/sdg_07_40.

20 Examens environnementaux de l'OCDE : Luxembourg 2020 https://www.oecd-ilibrary.org/environment/examens-environnementaux-de-l-ocde-luxembourg-2020_91951f4d-fr

Partie 2

Les études sur la productivité par STATEC Research

Cette partie comporte quatre études rédigées en anglais et réalisées par STATEC Research pour le compte du CNP. La première contribution présente certains résultats de la dernière mise à jour du projet LuxKLEMS, documentant l'évolution de la productivité du travail et de la productivité totale des facteurs pour le Luxembourg. La deuxième étude aborde l'accumulation et la composition du capital intangible et sa contribution à l'évolution de la productivité du travail dans l'économie marchande luxembourgeoise. La troisième contribution étudie la relation entre des pratiques managériales et la performance des entreprises au Luxembourg. La quatrième étude explore le rôle des systèmes nationaux d'innovation dans la production d'innovations.

2.1
Introduction

Part 2 of the report presents selected studies from the analysis of Luxembourg's productivity conducted at STATEC Research in the last year.

The studies illustrate the evolution of labour and total factor productivity for the Luxembourg's economy, from 1995 to 2021 (or the latest available observation). They are part of a research programme that place emphasis on the investigation of the determinants of productivity, as understanding the sources of productivity growth is important from both a scientific and policy viewpoint. Specifically, they focus on the role of intangible capital as a source of productivity growth.

The term "intangible capital" captures those inputs to production that do not possess "a physical or financial embodiment" (OECD). As opposed to traditional capital – which comprises buildings, machinery and equipment – intangible capital includes organizational, human, and digital capital, as well as the output of Research and Development (R&D) and innovation activities. Also referred to as knowledge capital, intangibles have become a focus of productivity studies and policy analysis in recent years, which has also been made possible by improved data availability. The growth in the accumulation of intangible assets, which has accompanied the increasing relevance of service industries in advanced economies, is a well-documented trend.

In line with the recent advances in this field of research, two studies in this chapter exploit data from STATEC and an international research consortium to investigate the relation between productivity and, respectively, firms' managerial practices and the stock of intangible capital in Luxembourg. This is relevant to Luxembourg for two reasons: firstly, productivity figures might be biased by the non-inclusion of intangibles in productivity accounts; secondly, intangibles are particularly relevant for service economies. The remaining studies provide evidence on R&D and innovation activities in the country, and illustrate productivity patterns for economic activities classified according to a R&D "intensity" taxonomy.

The reader should note that the studies adopt different methodologies and exploit different sources of data. As a result, the definition of productivity differs across the contributions. Thus, while overall patterns are broadly aligned, specific yearly figures might differ. For instance, the cross-country research on intangibles defines labour productivity as the ratio of value added to hours worked, while LuxKLEMS compiles productivity indicators by comparing gross output to labour (hours worked), capital stock, and intermediate consumption. The research on management practices takes a firm-level perspective and measures labour productivity in terms of both turnover and value added per person employed. The economic aggregates considered are the total economy and broad aggregates such as manufacturing and service industries.

The first of the four contributions, in section 2.2, illustrates selected results from the latest update of the LuxKLEMS project, documenting the evolution of labour and Total Factor Productivity (TFP) for Luxembourg. A STATEC initiative, which dates back more than a decade, LuxKLEMS uses data from STATEC's National Accounts to compile and update annual productivity indicators. To do so, it uses a frontier approach, which means that it compares the resources (inputs) used in production – capital, labour, and energy, material and services – to the goods and services produced for all Luxembourg industries. This comparative exercise provides information on the productive performances of industries and industries aggregates. It also allows us to examine the sources of productivity growth. Specifically, it focuses on the roles of inputs accumulation per worker (referred to as input deepening), efficiency gains and technological progress in shaping productivity patterns. Efficiency gains refer to improvements in the way that industries use and combine their resources, while technological progress indicates an expansion of the economy's production possibilities. Findings show that productivity patterns for the whole economy are volatile, feature weak growth, and track those of service industries, reflecting the weight of services in the total economy. The slowdown in labour productivity growth is associated to poor TFP performances. The analysis reveals that the growth of labour productivity in services is associated to input deepening, while TFP growth, and specifically technological change, is a predominant source of productivity growth in manufacturing. The most recent years show a recovery in labour productivity growth, but this should be interpreted with care due to data revisions. LuxKLEMS also delivers productivity indicators for industries classified according to their Research and Development intensity, and indicates that aggregate productivity patterns are mainly accounted for by low R&D-intensive services in Luxembourg.

The second contribution, in section 2.3, analyses the accumulation and composition, as well as the contribution to labour productivity growth, of intangible capital for Luxembourg's business economy. Intangible capital is difficult to estimate and is only partially captured by datasets for economic analysis or official statistics. This can lead to a bias in estimates of productivity levels and growth rates. The study attempts to address this issue by exploiting a new cross-national dataset, EUKLEMS-IntanPROD. These data contain detailed information on intangible assets by type for Member States of the European Union and other advanced economies, enabling cross-country comparisons. The analysis of the share and composition of the country's intangible stock shows that the share of intangible capital is comparatively low in Luxembourg. Over the period from 1995 to 2019, the accumulation of intangible assets has been slower than in other advanced economies. There has also been a noticeable shift in its composition, which saw a decline in the share of new financial products in face of an increase in branding and organizational capital.

What's more, accounting for intangibles affects the estimates of labour productivity growth. Their contribution to productivity growth is comparatively low in Luxembourg. However, the explicit consideration of intangibles in productivity accounts mitigates the slowdown in labour productivity growth observed after the great recession of 2008-2010.

The third contribution, in section 2.4, investigates the relationship between management practices (MPs) and firm performance in Luxembourg's manufacturing and business services. Managerial practices denote managerial structures or talent within organizations. This issue has received considerable attention in the economic literature. Findings from mainstream research indicate a positive association between management quality and performance. Despite the relevance of these relationships, firm-level evidence for Luxembourg is lacking. The study partially fills this gap using data from the Community Innovation Survey (CIS) and Structural Business Statistics (SBS). Notably, the CIS 2018 wave for Luxembourg included questions on two MPs inspired by recent literature on the topic. Thus, following a well-established research stream, these data allow an assessment of the association between MPs importance and enterprise performance in terms of labour productivity. Results from regression analysis suggest that firms that consider MPs as important for their business tend to have higher productivity. This holds after controlling for other factors, such as workforce education and enterprise group affiliation. However, this analysis does not imply a causal effect of MPs importance on productivity.

The fourth and last research article, in section 2.5, focuses on the "production" of innovation. Specifically, the analysis considers the link between innovation inputs – the number of researchers and R&D expenditures – and innovation outcomes, namely patents and scientific articles. The articles shows that innovation outcomes are significantly influenced by National Innovation Systems. National Innovation System includes resources such as the amount of training, the extent of university-industry or cross-industry collaboration, and intellectual property rights. Using a computational frontier approach, the article shows that cross-country differences in National Innovation Systems account for a significant share of relative inefficiencies in producing innovation from typical innovation inputs. This finding suggests that countries can foster economic growth by strengthening National Innovation Systems.

2.2
LuxKLEMS: Productivity trends and drivers in Luxembourg

2.2.1
Introduction

The LuxKLEMS initiative, led by the National Institute of Statistics and Economic Studies of Luxembourg (STATEC), has been providing productivity figures for the country for over a decade (DiMaria and Ciccone, 2008; Peroni, 2012; Peroni et al., 2020). LuxKLEMS compiles yearly indicators of labour and total factor of productivity (TFP), productivity drivers, and inputs and output to production for the Luxembourg's economy from STATEC's National Accounts data. This contribution presents main results from the latest LuxKLEMS update, based on the National Accounts' release of September 2022. It focuses on the evolution of labour and TFP from 1996 to 2021 for the total economy and two broad aggregates of economic activities, and examines key drivers of productivity growth, namely input deepening, efficiency improvements, and technological changes.

In light of the relevance of research & development (R&D) activities for innovation output, technological changes and, thus, productivity, this contribution also presents productivity indicators for industries "clustered" according to an R&D intensity-based classification of industries proposed by the OECD (Galindo-Rueda and Verger, 2016). R&D intensity reflects the proportion of each industry's R&D expenditure in relation to its gross value added (GVA). We consider two classes, namely low (denoted throughout by LRD) and medium and high R&D intensity classes (denoted by MHRD) for both service and manufacturing industries. This allows us to explore (differences in) the productivity performances of the various classes of industry. (To our knowledge, there exists no study that compare productivity indicators by R&D intensity across OECD countries.)

Indeed, the relationship between R&D, innovation, and productivity, while generally accepted as positive, is an ongoing subject of investigation and debate. Economists argue that R&D-driven innovation fosters economic growth (Romer, 1990). Griliches (1979, 1998), Hall (2011), and Nelson and Winter (1982) note that R&D investments prompt innovation, leading to enhanced competitiveness and productivity. Criscuolo et al. (2008) illustrate how innovation might drive productivity. Asikainen (2008) provides evidence for the case of Luxembourg. Nonetheless, the Solow paradox (1987) highlights that, despite increased R&D expenditure and innovation, productivity gains are not always apparent in the case of Information and Communication Technologies. Similarly, Brynjolfsson (1993) suggests that technological advancements do not necessarily guarantee boosts to productivity (see Syvverson, 2011, for a review).

In this contribution, labour productivity is defined as gross output per hour worked. TFP represents the ratio of gross output to a combination of inputs: capital, labour, and intermediate consumption, which includes energy, materials, and services. Input deepening and TFP growth drive labour productivity growth. Input deepening denotes the increase in inputs relative to labour, while TFP growth indicates a rise in output for a given input level, resulting from enhanced input utilisation through efficiency change and/or technical progress due to improved production techniques.

The contribution provides results for broad aggregates of economic activities to capture the differences in the nature of production across industries groups. These aggregates are the total economy, and two broad group of industries referred to as manufacturing and services.

This contribution is organised as follows: Section 2 presents the LuxKLEMS framework. Section 3 presents the evolution of labour productivity and its drivers for the total economy, services, and manufacturing. Section 4 outlines trends in TFP and its drivers for the total economy and main aggregates of industries. In Section 5, the report presents the contribution of various R&D intensive classes to productivity indicators in manufacturing and services. Section 6 concludes.

The findings show that labour productivity has slowed down over the last decade. For the total economy and services, input deepening is the key driver of labour productivity growth, while manufacturing productivity growth relies on TFP, primarily driven by technical changes. In addition, given the ongoing debate on the role of R&D and innovation on productivity, the report uses the OECD's R&D intensity taxonomy to classify industries into low or medium/high intensity, examining their contribution to productivity. Results indicate that low R&D intensity industries primarily influence productivity in the service sector, while the manufacturing sector's productivity is mainly driven by medium/high R&D intensity industries.

2.2.2
The LuxKLEMS framework

As already mentioned, LuxKLEMS provides productivity indicators compiled from STATEC's National Accounts. STATEC's National Accounts are a comprehensive system of accounts and balance sheets, which provide a framework to describe Luxembourg's economy. These accounts align with the European System of Accounts (ESA 2010) and the Statistical classification of economic activities in the European Community (NACE Rev. 2) in terms of definitions, classifications, and accounting rules. These features of National Accounting enable standardized international comparisons of economic performance across countries and over time, thus facilitating a robust analysis of European economic activities.

LuxKLEMS adopts the frontier approach of Data Envelopment Analysis (DEA), originally developed by Charnes et al. in 1978, to compute productivity indicators.[1] This framework provides a breakdown of productivity changes into the separate components of technical change and efficiency change (see e.g. DiMaria and Ciccone, 2007).

In assessing productivity, the LuxKLEMS methodology differentiates from typical frameworks. While most focus on basic inputs like labour and capital, KLEMS also incorporates energy, materials, and services (EMS) as inputs to production. This necessitates using gross output (in volumes) instead of value added as a measure of production. This is particularly relevant for Luxembourg, a small open economy, where intermediate consumption represents a large and increasing share of output (see Figure 12 in the Appendix).[2] Thus, in LuxKLEMS, labour productivity is defined as gross output per unit of labour (hours worked).

Another feature of the LuxKLEMS framework is that it provides productivity indicators at the industry level for 30 types of economic activities. These 30 industries cover the whole range of economic activities performed in Luxembourg according to the NACE Rev. 2 classification at the two-digit level. Productivity indicators at the industry level are then aggregated to obtain overall indicators for services, manufacturing, and the total economy, using weights that reflect each industry's contribution to its respective sector's total output. Note that throughout this contribution, "manufacturing" includes manufactured products, agriculture, utilities, and construction. "Services" is comprised of business services, financial activities, and non-market services.

Box 1
Decomposition of productivity indicators

In the LuxKLEMS framework, labour productivity is defined as gross output per hour worked. Assuming there are three inputs: labour, capital, and energy, a Cobb-Douglas production function can be written as:

$$Q_t = A_t K_t^{\alpha} E_t^{\beta} L_t^{1-\alpha-\beta}, \alpha + \beta < 1 \qquad (1)$$

where *t* denotes time (year), *Q* gross output, *A* a technology parameter. Capital *(K)*, labour *(L)*, and energy *(E)* are the inputs to production. Equation (1) suggests that with constant inputs, a rise in output corresponds to an increase in the technology parameter *(A)*, known as total factor productivity (*TFP*). A version of this model by Aigner et al. (1977) augmented by efficient input utilization is as follows:

$$Q_t = \underbrace{A_t K_t^{\alpha} E_t^{\beta} L_t^{1-\alpha-\beta}}_{\text{Production frontier}} \times \underbrace{exp(Ef_t)}_{\text{Efficiency term}} \qquad (2)$$

The first component of this equation represents the technological frontier, which gives the highest achievable output given inputs use and technology. If A_t rises due to technical advancements, this frontier shifts upward, enabling economies to produce more output from the same inputs use, or to maintain output levels with fewer inputs. Yet, not every economic entity optimally performs; some might not obtain their maximum potential output for their given inputs. Such entities, not fully using available technology, are termed inefficient and fall below this frontier, which explains the introduction of the efficiency term. Dividing both sides of equation (2) by hours worked and then taking the log first difference (i.e. *dln*) allows us to derive an equation for productivity growth:

$$\underbrace{dln\left(\frac{Q_t}{L_t}\right)}_{\text{Labour productivity growth}} = \underbrace{dln(A_t)}_{\text{Technical change}} + \overbrace{(Ef_{t+1} - Ef_t)}^{\text{Efficiency change}} + \underbrace{\alpha \times dln\left(\frac{K_t}{L_t}\right) + \beta \times dln\left(\frac{E_t}{L_t}\right)}_{\text{Input deepening}} \qquad (3)$$

Equation (3) shows that labour productivity growth (based on gross output per hour work) can be decomposed into technical change, efficiency change and input deepening.

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[1] We adopt DEA primarily for its advantages in measuring productivity across industries with diverse input mixes, for the robustness of indicators to revisions, and because it allows us to produce indicators when the availability of observations is limited. Unlike parametric methods, DEA does not impose any functional form on the production frontier (which, broadly speaking, represents production possibilities according to the overall technological level), except for assumptions on returns to scale. Using DEA also minimizes the impact of data revisions on the indicators produced from previous data vintages.

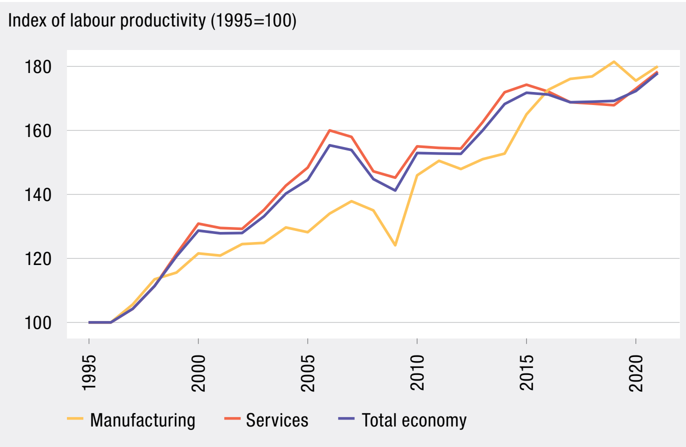
[2] Gross output is the sum of value added and intermediate consumption.

2.2.3
Trends of labour productivity and its components

Labour productivity is one of the key indicators for measuring economic performance (OECD, 2023). In LuxKLEMS, labour productivity is defined as gross output per unit of labour (hours worked). In this section we present trends of labour productivity for Luxembourg's total economy, and services and manufacturing industries, for the period 1995-2021 (Figure 1). Then, for each aggregate we examine the contribution of TFP growth and input deepening to labour productivity growth (Figure 2). Input deepening measures changes in the quantity of inputs per hour of work, whereas TFP quantifies the output-to-input ratio. Box 1 presents the decomposition of productivity indicators used in this contribution.

Labour productivity exhibits an overall upward trend over time, until the mid-2010s. The trend reflects the double-dip recession, featuring a marked decline during the financial crisis, followed by a recovery. Since 2015, it flattens out, moving upwards again in the two last years of observation. As expected, total economy's productivity patterns closely follow those of service industries, as services account for over 80% of the total economy's output (see Table 1). The productivity performance of manufacturing is weaker than the one of services. Post-recession recovery followed by a period of sustained growth reverse this tendency from 2016 onwards.

Figure 1
Trend of labour productivity: total economy, services, and manufacturing (1995-2021)



Source: Authors' calculations from Statec data

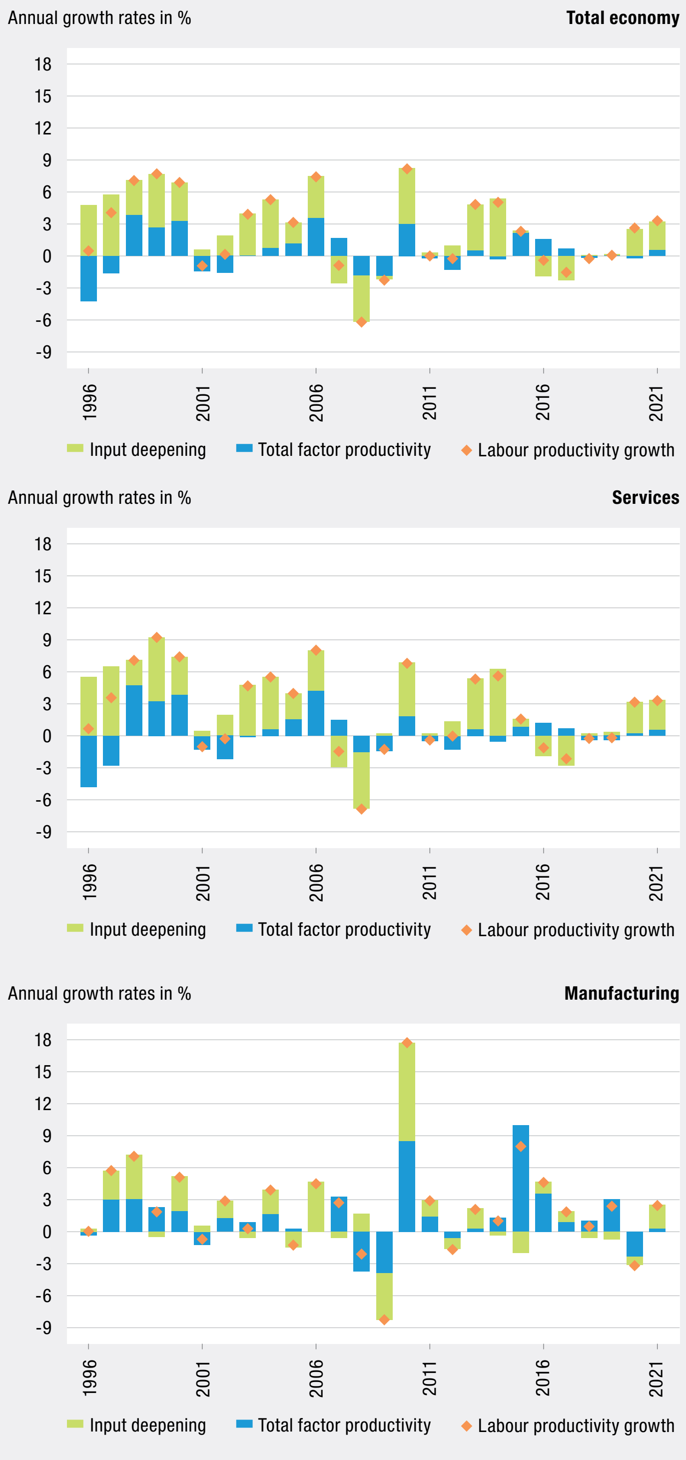
Panels in Figure 2 present annual growth rates for labour productivity and its components, namely input deepening, and TFP from 1996 to 2021 across Luxembourg's total economy and major aggregates. The data indicate pronounced volatility in labour productivity growth, with occurrences of negative growth. Following the 2007-2009 crisis, labour productivity growth slows down compared to previous decades, mirroring trends in other OECD countries (Andrews et al., 2016). While patterns of labour productivity growth in the total economy and services sectors align, manufacturing differentiates. The fall in labour productivity growth during the 2007-2008 crisis was especially noticeable in this sector, and volatility has been somewhat more pronounced. Following the crisis, however, the manufacturing industries experienced a rapid recovery, leading them to converge with services' productivity performances by 2016. Overall, we notice that labour productivity patterns in total economy and services industries are primarily accounted for by changes in input deepening, while manufacturing's productivity reflects TFP growth patterns.

The examination of TFP growth patterns shows considerable fluctuations for the total economy and services. Recent trends show weak, close to zero TFP growth. In contrast, TFP growth in manufacturing has been more sustained, except for a few years, such as around the bursting of the IT bubble (2001-2002) and the financial crisis (2007-2008), becoming a dominant force driving labour productivity growth in this sector.

The next section explores TFP and its components in greater detail.

Figure 2

Labour productivity growth and drivers: total economy, services, and manufacturing (1996-2021)



Note: Figures in the chart represent yearly growth rates. Detailed numerical data for this figure can be found in Tables 2-4 in Appendix.
Source: Authors' calculations from Statec data

2.2.4 Trends of total factor productivity, efficiency and technical change

Total factor productivity (TFP) is another key indicator of economic performance of economic units. Defined as the ratio of output to inputs (Farrell, 1957), TFP reflects the overall ability of economic entities of transforming all inputs into output, i.e., goods and services.[3] TFP is driven by technological improvement and efficiency gains. In what follows, we present trends and growth rates of TFP for Luxembourg's total economy, services, and manufacturing for 1995-2021,[4] highlighting efficiency gains and technical change.

In LuxKLEMS, TFP changes are compiled using the Malmquist index (Caves et al. 1982), which captures both technical and efficiency changes by being a geometric mean of these two components (Färe et al., 1994). Efficiency measures how well inputs are used to produce output, by comparing an entity's output to the maximum potential output (a distance) corresponding to the same input levels for a given period. Efficiency gains represent how distances evolve over time. Technological change measures the difference in maximum output between the current and previous periods, for given input levels.

Broadly, technical change captures improvements in production technology and input quality (e.g. Kumbhakar et al., 2015). Conversely, efficiency change indicates improvement of input use during production.[5] Decomposing TFP into its two components provides insights into the sources of productivity growth. Thus, this section also presents growth rates of efficiency and technical changes and their contributions to TFP growth in Luxembourg's total economy, services, and manufacturing from 1996 to 2021.

Aggregated measures of TFP for each year are derived using a bottom-up approach, which involves calculating industry-level Malmquist TFP growth rates, then aggregating them to national or main aggregates figures using production values as weights (Zelenyuk, 2006). Box 2 provides further details.

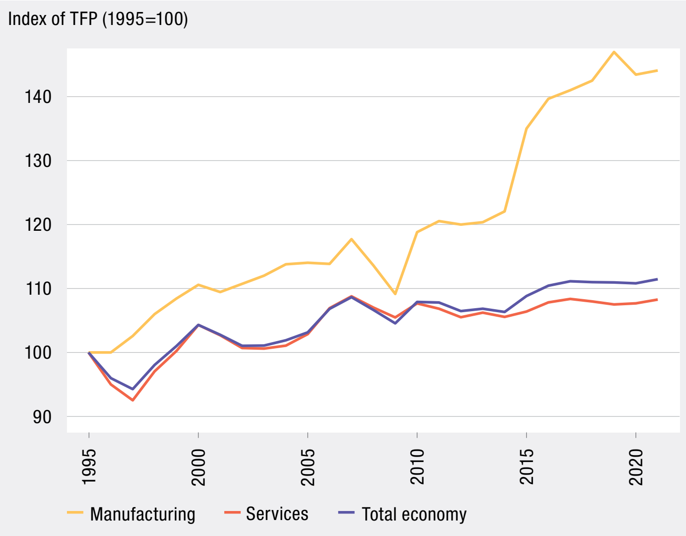
3 Typically, in growth accounting, TFP growth measures the part of output growth not attributed to changes in the volume of inputs (OECD, 2023).

4 The forthcoming LuxKLEMS report includes an appendix on industry-level measures of productivity, providing insights into factors driving productivity growth in each industry.

5 This can be achieved through refined management practices, improved worker training (Wang et al., 2016; Ali et al., 2012), and measures that optimise operations and resource allocation.

Figure 3 presents the evolution of TFP indices for Luxembourg's main aggregates. Once again, the total economy's trend mirrors the one for services. Although manufacturing faces a steeper downturn during the financial crisis, its rapid recovery leads to a more sustained upward TFP trend, markedly different from services.[6]

Figure 3
Trend of TFP: total economy, services, and manufacturing (1995-2021)

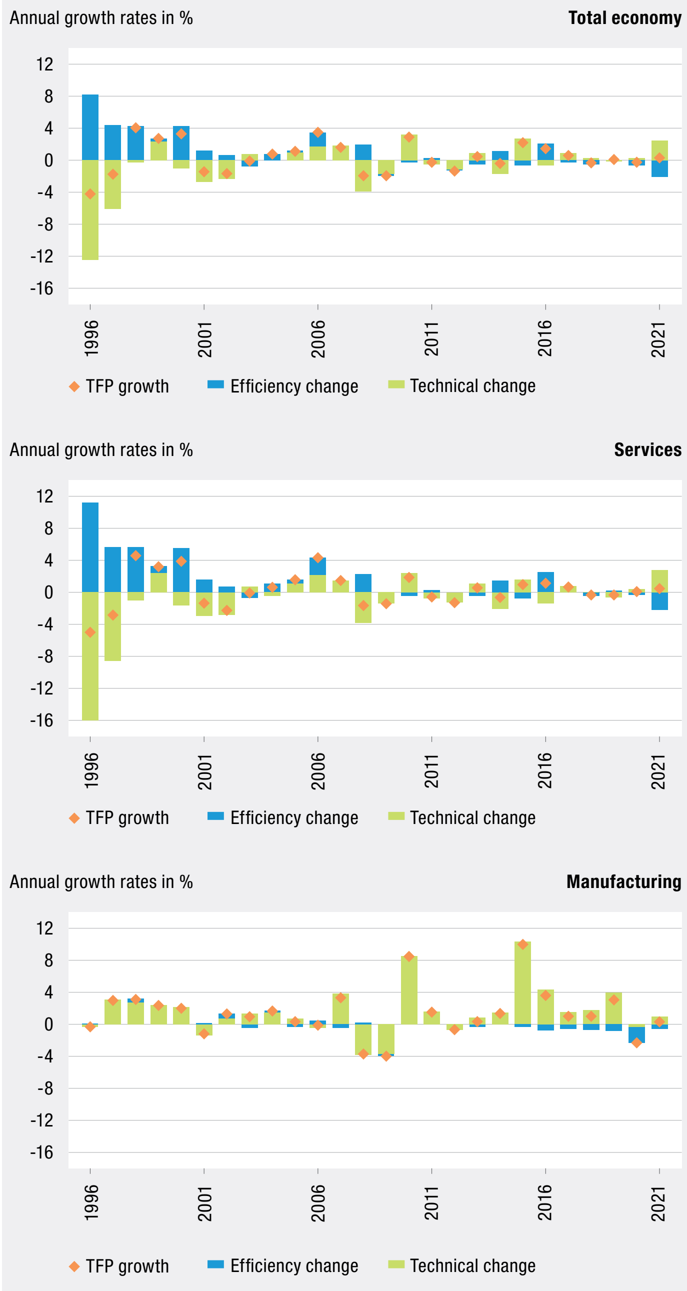


Source: Authors' calculations from Statec data

The panels in Figure 4 present annual growth rates of TFP, efficiency change, and technical change for the main aggregates. TFP growth is low in the total economy and services, but it is sustained in manufacturing. The pattern of efficiency and technical change for the total economy and services sectors are clearly comparable, whereas the manufacturing sector differentiates.

The figure suggests that, overall, technical change is the primary driver of changes in TFP for the total economy. Conversely, efficiency change has had a more modest impact on TFP growth. When looking at the main sectors of the economy, technical change appears the predominant driver of productivity in manufacturing. In services, changes in efficiency are also sizable and partially offset (negative) technical changes.[7] Service industries typically exhibit larger efficiency gains than manufacturing, but these gains have decreased over time. In manufacturing, the contribution of efficiency change to TFP growth is notably smaller than in services, and mainly negative or negligible in the recent decade.

Figure 4
TFP growth and drivers: total economy, services, and manufacturing (1996-2021)



Note: Detailed numerical data corresponding to this figure can be found in Tables 2-4 in Appendix.
Source: Authors' calculations from Statec data

6 The trend for manufacturing should however be interpreted with care in light of a structural break in underlying business statistics for 2014 and 2015.

7 Negative TFP growth is due to technical regress or losses in efficiency. Negative technical change is typically difficult to interpret. On this, one can see Peroni et al. (2020), where authors discuss an explanation based on demand and capacity utilization rates, and references therein.

Box 2
Compilation of aggregate TFP

Following Zelenyuk's (2006) approach, in LuxKLEMS we first compile productivity indicators at the industry level, then we aggregate them into broader categories, such as manufacturing, services, and the total economy. The approach involves aggregating TFP Malmquist Indices as a weighted geometric mean of individual industries, according to the formula:

$$TFP = \left(\frac{\pi_{i=1}^{N} D_t^i(y_{t+1}^i, x_{t+1}^i)^{s_{t+1}^i}\, \pi_{i=1}^{N} D_{t+1}^i(y_{t+1}^i, x_{t+1}^i)^{s_{t+1}^i}}{\pi_{i=1}^{N} D_t^i(y_t^i, x_t^i)^{s_t^i}\, \pi_{i=1}^{N} D_{t+1}^i(y_t^i, x_t^i)^{s_t^i}}\right)^{0.5} = \pi_{i=1}^{N} TFP^i \quad (1)$$

With:

$$TFP^i = \left(\frac{D_t^i(y_{t+1}^i, x_{t+1}^i)^{s_{t+1}^i} D_{t+1}^i(y_{t+1}^i, x_{t+1}^i)^{s_{t+1}^i}}{D_t^i(y_t^i, x_t^i)^{s_t^i} D_{t+1}^i(y_t^i, x_t^i)^{s_t^i}}\right)^{0.5}$$

In this formula, t represents a specific year, i denotes industries, and D indicates distance functions. Distances measure the difference between an industry's actual performance (given its input bundle x and output y) and the best possible performance considering the available technology. For example, $D_t^i(y_t^i, x_t^i)$ measures an industry's performance in year t relative to the best performance achieved by other industries in the same year, taking into account the inputs used. Similarly, $D_{t+1}^i(y_{t+1}^i, x_{t+1}^i)$ evaluates the industry i's performance in year $t+1$, taking into account its inputs used, relative to best performing industries in year $t+1$, and so forth. S denotes the weights assigned to industries' distance functions. The choice of weight is important as it significantly affects the evolution of aggregate values. To assign weights, we compute TFP Malmquist Indices using different weights and compare them with Eurostat data. Our findings indicate that the optimal weights are based on each industry's output share in the total output of its respective sector. This means that when computing aggregates for manufacturing and services, different weights are applied.

Taking the logarithm of both sides of Equation (1) gives the aggregated Malmquist TFP growth rate as:

$$ln\,(TFP) = ln\,(\pi_{i=1}^{N} TFP^i) = \Sigma_{i=1}^{N}\, ln\,(TFP^i) \quad (2)$$

Equation (2) implies that the aggregated TFP growth equals the sum of TFP growth rates of all individual industries.

2.2.5
Productivity and R&D intensity

In light of the relevance of R&D activities for innovation output and productivity, both central subjects in economic debates and policy-making, this section uses the OECD's R&D intensity-based classification of industries to assess their contributions to productivity trends in Luxembourg. Specifically, this analysis aims to illustrate which R&D intensity classes drive productivity and economic growth within service and manufacturing in Luxembourg.

Following the OECD's R&D intensity classification proposed by Galindo-Rueda and Verger (2016), we have assigned Luxembourg's industries to two groups: low (LRD) and medium/high (MHRD). Increasing R&D intensity is a policy target according to the Europe 2020 strategy (Parvan et al., 2021). In 2019, however, Luxembourg R&D intensity was 1.19%, placing it 19th in the European Union and slightly below the 2% European average. The unique structure of Luxembourg's economy, where 73% of R&D activities are led by large firms[8] (Parvan et al., 2021) may be one of the possible explanations for this below-average R&D performance. Box 3 provides more information on OECD's R&D intensity taxonomy.

Box 3
OECD R&D intensity taxonomy

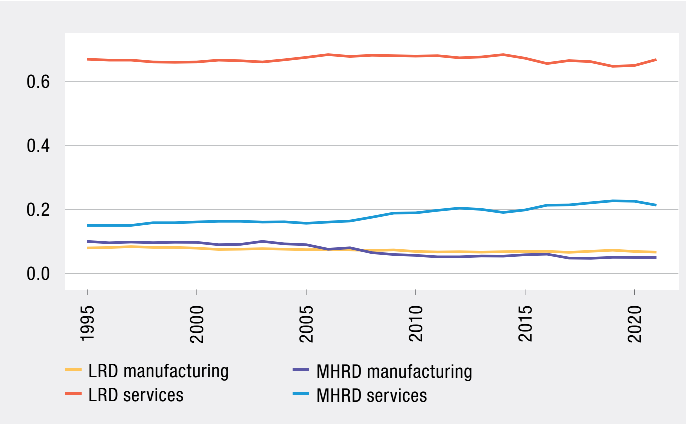
A taxonomy provides a structured framework for classifying information in a hierarchical manner, facilitating its interpretation. For instance, in National Accounts, the NACE classification classify industries based on their resources (inputs), production methods, and outputs (goods and services).

In 2016, at the OECD, Galindo-Rueda and Verger proposed an industry classification based on R&D intensity, following Hatzichronoglou's 1997 research. This classification primarily reflects a weighted average of industry-level R&D expenditures across a majority of OECD countries and partner economies (i.e. Taipei and Singapore). Weights are value added in purchasing power parities (PPP). This classification identifies industries that generally allocate significant funds towards R&D in relation to their gross value added. The driving force behind these R&D expenditures often comes from two key reasons: the industries either use high-technology production processes or produce high-tech goods and services. The classification is used in this context to provide an indication of the technological "level" or "content" of industries. (Indeed, it is plausible that, even if not engaging directly in R&D, belonging to a class could be useful in indicating the technological potential for given industries.

[8] Large firms refer to companies with 250 or more employees; there were approximately 200 such firms in Luxembourg in 2019.

Table 1 lists Luxembourg's manufacturing and services industries and their R&D intensity classes. It also displays their respective average annual shares in national output. Figure 5 illustrates the annual evolution of the shares of LRD and MHRD intensive industries in the total output for both sectors. (These shares sum to one every year.) LRD intensive industries account for about 80% of the total output produced. This includes a substantial contribution from LRD activities in services, which alone account for about 70% of the total economy's output, and 10% in manufacturing. MHRD intensive industries account for approximately 20% of the remaining output, with both manufacturing and services industries contributing roughly 10% or less to the total output of the economy. These statistics highlight the dominant role of the services sector, particularly LRD services, in driving Luxembourg's gross output.

Figure 5
Evolution of share of services' and manufacturing's output in total output by R&D intensity



Note: Y-axis values are in decimals; to convert to percentages, multiply by 100.
For example, 0.6 = 60%.
Source: Authors' calculations from Statec data

In what follows we present labour productivity trends for manufacturing and service industries, classified by their R&D intensity classes. Figure 6 specifically illustrates these trends from 1995 to 2021, distinguishing between four industry groups: LRD services, MHRD services, LRD manufacturing, and MHRD manufacturing.

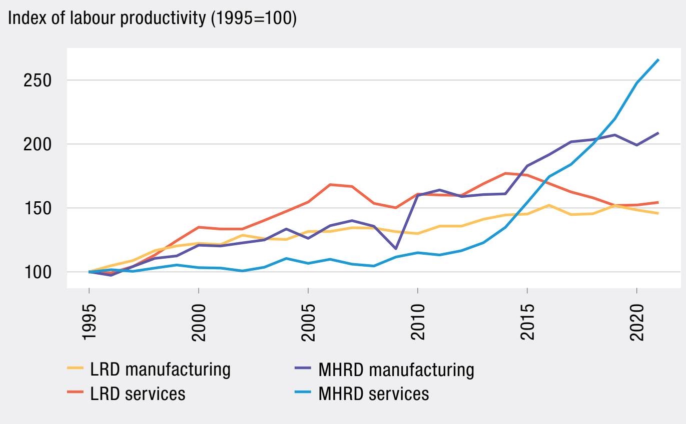
Overall trends are possibly dominated by LRD services, at least until 2016. Before 2016, LRD service industries displayed a higher labour productivity trend than their MHRD counterparts. However, in 2016 MHRD service productivity overturned LRD, with the gap in performance continuing to widen afterwards. In manufacturing, prior to the financial crisis, LRD industries have been outperforming MHRD industries. However, following the crisis, MHRD industries experienced a rapid and substantial recovery, leading to a divergence in their labour productivity levels from LRD industries. This divergence has persisted or even accelerated in the subsequent years, as MHRD industries outperformed their LRD counterparts. Thus, in both service and manufacturing, in recent years the MHRD industries have been outperforming LRD industries in terms of productivity dynamism. To understand the underlying reasons for these trends, additional analysis would be required.

Table 1
Research and development (R&D) intensity by industries in Luxembourg

Industry	Name	R&D intensity class	Average annual share in total gross output
Manufacturing, Agriculture, Utilities, and Construction (NACE Rev. 2 sections: A, B, C, D, E, and F)			
	Agriculture	Low	0.32
	Forestry	Low	0.02
	Mining and Quarrying	Medium/high	0.08
	Food, Textiles, Paper & wood, Petroleum	Medium/high	2.39
	Chemicals and pharmaceuticals	Medium/high	0.25
	Other manufacturing	Medium/high	6.81
	Electricity and gas	Low	0.85
	Water supply	Low	0.09
	Waste management	Low	0.36
	Construction	Low	4.42
Business services, Financial activities, and Non-market services (NACE Rev. 2 sections: G, H, I, K, L, M, N, O, P, Q, R, S)			
	Wholesale and retail trade	Low	6.86
	Transport and postal activities	Low	3.43
	Accommodation and food services	Low	1.36
	Publishing activities	Low	0.98
	Telecommunications and IT services	Medium/high	4.47
	Financial service activities	Low	33.97
	Insurance, reinsurance & pension funding	Low	1.99
	Activities auxiliary to financial services & insurances	Low	13.79
	Real estate activities	Low	3.38
	Services to business and R&D	Medium/high	5.00
	Rental, Leasing, Employment, Travel agency, Others	Low	1.88
	Public administration	Low	2.58
	Education	Medium/high	1.64
	Health services	Medium/high	1.48
	Social work activities	Low	0.84
	Arts and entertainment activities	Low	0.20
	Sport activities	Low	0.15
	Activities of membership organizations	Low	0.21
	Repair of computers and personal & household goods	Low	0.02
	Other personal services	Low	0.19

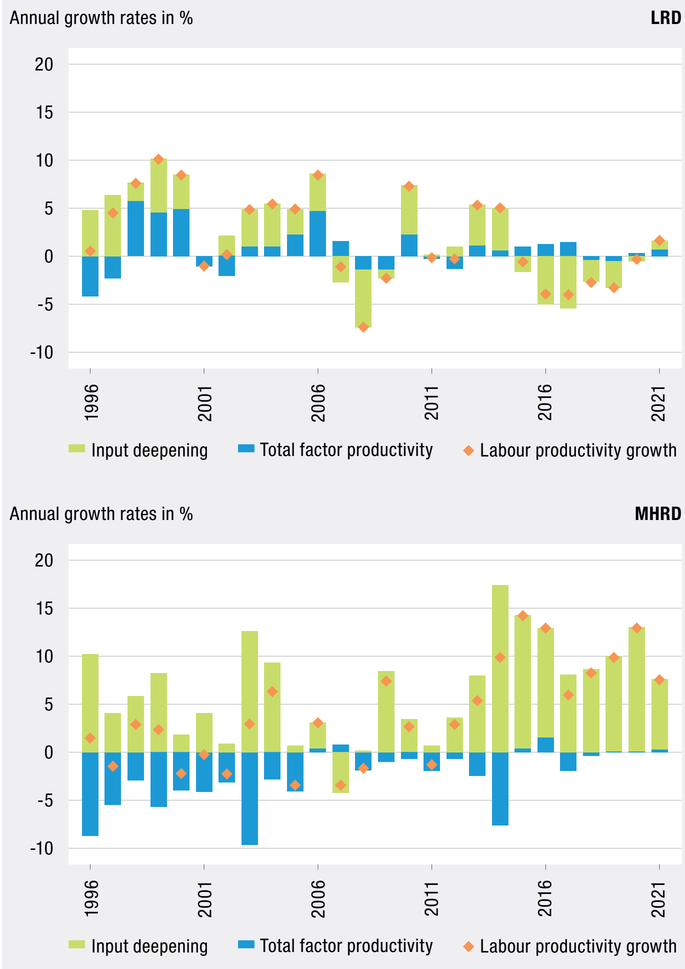
Note: Shares in the table are represented as decimals.
Source: Authors' calculations from STATEC data

Figure 6
Trend of labour productivity: services and manufacturing by R&D intensity (1995-2021)



Source: Authors' calculations from Statec data

Figure 7
Labour productivity growth and drivers in services by R&D intensity (1996-2021)



Note: Detailed numerical data corresponding to this figure can be found in Tables 5-6 in Appendix.
Source: Authors' calculations from Statec data

What follows provides an overview of the evolution of main drivers of labour productivity and TFP in Luxembourg for industries categorized by their R&D intensity classes. Panels in Figure 7 present annual growth rates from 1996 to 2021 for labour productivity, input deepening, and TFP across LRD and MHRD services. Figure 8 displays the same data for LRD and MHRD manufacturing industries.

Within services, MHRD and LRD display different patterns of labour productivity growth. In the MHRD services category, input deepening appears to sustain the growth of labour productivity throughout the period. In contrast, TFP growth is often negative. In the past decade, the growth in input deepening becomes even more marked, while TFP growth is close to zero, indicating a less negative growth. In the LRD services sector, labour productivity growth is more volatile and weaker, especially in the last decade when it features lower or even negative growth rates. This is essentially driven by negative input deepening. (In contrast, productivity growth in the first decade was driven by both positive TFP growth and input deepening.)

For the manufacturing sector, notably, irrespectively of their R&D intensity, both components — TFP and input deepening — have displayed varied impacts on labour productivity growth rates. No consistent dominant factor emerges, as their contributions have fluctuated over the years. The period around the financial crisis marked a crucial moment for MHRD manufacturing industries, with significant changes observed in both TFP and input deepening. Following the crisis, a notable recovery in the MHRD sector occurred explaining their divergence in labour productivity trends from LRD manufacturing industries observed in Figure 6.

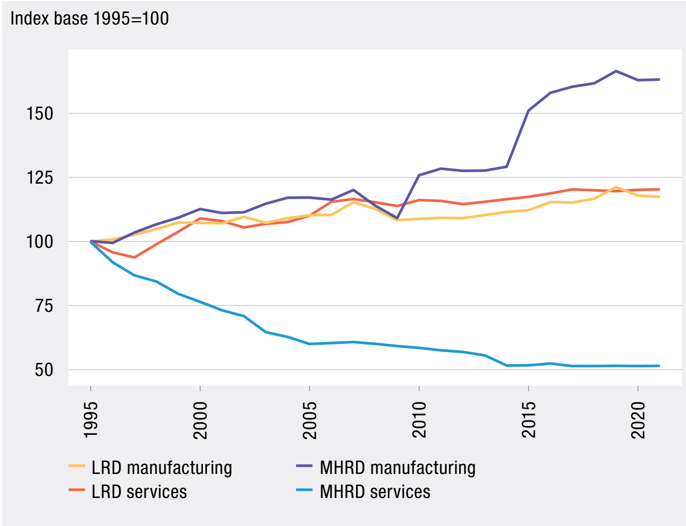
Figure 8
Labour productivity growth and drivers in manufacturing by R&D intensity (1996-2021)

Note: Detailed numerical data corresponding to this figure can be found in Tables 7-8 in Appendix.
Source: Authors' calculations from Statec data

Lastly, we present TFP trends for LRD and MHRD manufacturing and service industries. Figure 9 illustrates TFP trends from 1995 to 2021 for the four groups. Overall, up to 2009, all aggregates display similar and weak TFP trends, with the exception of MHRD service industries, for which data reveal a steady decline in TFP. Following the crisis, TFP for MHRD manufacturing exhibits a positive trend, which makes it stand out compared to the other industries.

Thus, Figure 9 suggests that the TFP trend in MHRD manufacturing industries is the primary contributor to the upward trend in manufacturing's TFP illustrated previously in Figure 3. Likewise, the main driver of services' TFP trend presented in Figure 3 is the LRD service industries.

Figure 9
Trend of TFP in services and manufacturing by R&D intensity (1995-2021)



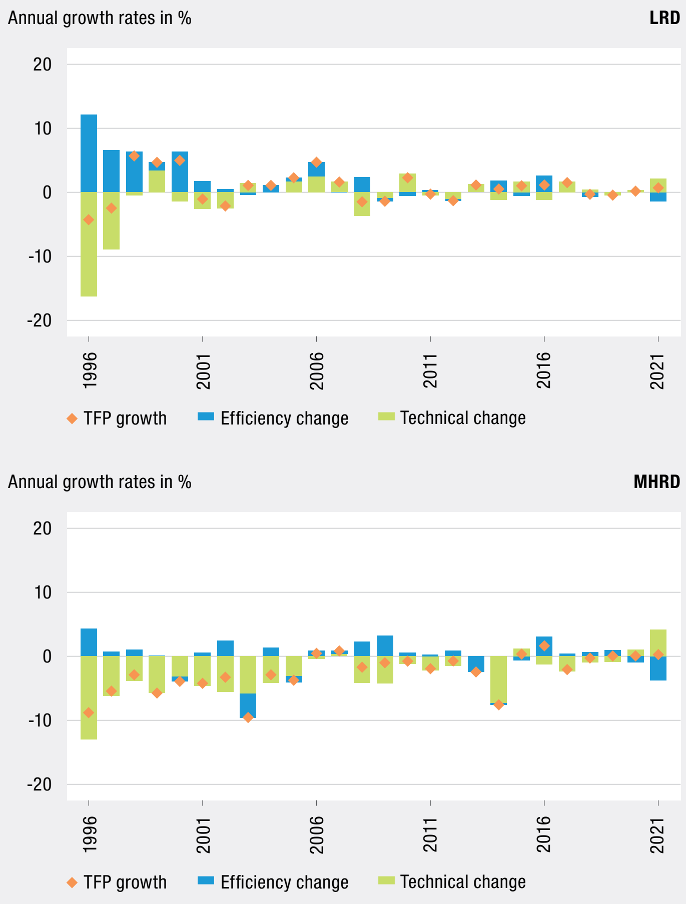
Source: Authors' calculations from Statec data

Figure 10 presents annual TFP, efficiency, and technical change growth rates from 1996-2021 across LRD and MHRD services. TFP growth in MHRD services can be attributed to negative technical change, as well as a lack of efficiency gains. In services, pre-crisis LRD industries exhibit weak and volatile TFP growth. LRD's services exhibit negative technical change, which offset considerable efficiency gains in the beginning of the period. This is followed by a period marked by some gains in efficiency. The trend flattens in correspondence of efficiency gains and technical changes, typically small in absolute values, offsetting each other.

Figure 11 displays the same statistics for LRD and MHRD manufacturing industries. Overall, in manufacturing, technical change is the key driver of TFP growth, with efficiency playing a minor role regardless of R&D intensity. Over the last decade, technical changes in MHRD have been mostly positive and sizeable (in contrast to some negative but small efficiency loss), which lies behind the sustained TFP trend of these industries.

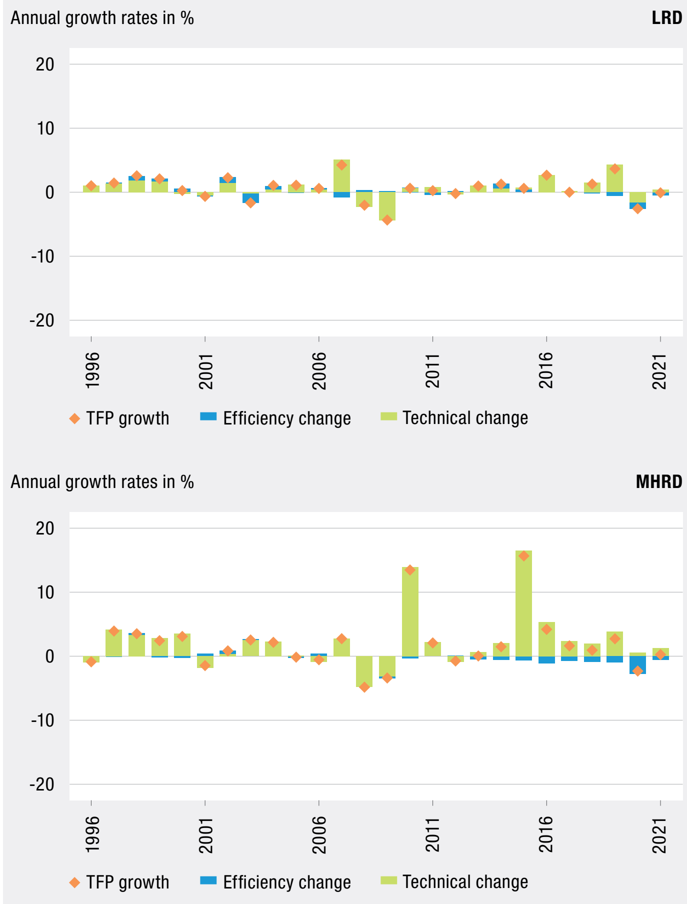
In summary, patterns of efficiency change, technical change, and TFP for LRD service industries drive productivity patterns observed in both service sector and the total economy. Given their significance, it is noteworthy that negative TFP growth in these industries generally results from technical regress, despite potential gains from positive efficiency changes.

Figure 10
TFP growth and drivers in services by R&D intensity (1996-2021)



Note: Detailed numerical data corresponding to this figure can be found in Tables 5-6 in Appendix.
Source: Authors' calculations from Statec data

Figure 11
TFP growth and drivers in manufacturing by R&D intensity (1996-2021)



Note: Detailed numerical data corresponding to this figure can be found in Tables 7-8 in Appendix.
Source: Authors' calculations from Statec data

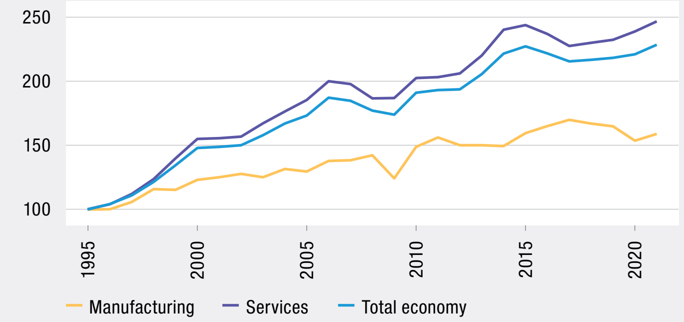
2.2.6 Conclusions

The latest STATEC's LuxKLEMS update provides productivity indicators for Luxembourg from 1995 to 2021. The focus is on labour productivity and total factor productivity (TFP) and their main drivers: input deepening, efficiency change, and technical change. LuxKLEMS present these indicators across the total economy, as well as for manufacturing and services industries. The findings show that labour productivity has slowed down over the last decade. For the total economy and services, input deepening is the key driver of labour productivity growth, while manufacturing' productivity growth relies on TFP, primarily driven by technical changes.

In addition, given the ongoing debate on the role of R&D and innovation on productivity, the report uses the OECD's R&D intensity taxonomy to classify industries into low or medium/high intensity, examining their contribution to productivity. Results indicate that low R&D intensity industries primarily influence productivity in the service sector, while the manufacturing sector's productivity is mainly driven by medium/high R&D intensity industries. Notably, 2021 saw a notable decline in the total economy efficiency, likely due to the disruptions of the Covid-19 pandemic.

2.2.7
Appendix

Figure 12
Evolution of intermediate consumption in total economy, services, and manufacturing (1995-2021)



Source: Authors' calculations from Statec data

Table 2
Total economy – Productivity growth and drivers (%) – 1996-2021

Year	Labour productivity	TFP	Efficiency change	Technical change	Input deepening
1996	0.51	-4.27	8.14	-12.41	4.79
1997	4.06	-1.64	4.42	-6.06	5.70
1998	7.06	4.09	4.26	-0.17	2.98
1999	7.70	2.71	0.32	2.39	4.99
2000	6.93	3.34	4.27	-0.92	3.58
2001	-0.91	-1.46	1.16	-2.62	0.55
2002	0.28	-1.59	0.68	-2.26	1.86
2003	3.95	-0.01	-0.77	0.77	3.96
2004	5.27	0.73	0.85	-0.12	4.54
2005	3.14	1.19	0.19	1.00	1.94
2006	7.45	3.55	1.79	1.76	3.90
2007	-0.85	1.71	-0.08	1.80	-2.56
2008	-6.17	-1.85	1.95	-3.80	-4.32
2009	-2.20	-1.88	-0.21	-1.66	-0.32
2010	8.14	2.96	-0.24	3.20	5.18
2011	0.09	-0.21	0.21	-0.43	0.30
2012	-0.20	-1.24	-0.13	-1.11	1.04
2013	4.82	0.49	-0.45	0.94	4.33
2014	5.01	-0.38	1.23	-1.62	5.40
2015	2.33	2.19	-0.52	2.71	0.14
2016	-0.33	1.54	2.08	-0.54	-1.87
2017	-1.51	0.73	-0.13	0.86	-2.24
2018	-0.20	-0.25	-0.49	0.24	0.05
2019	0.18	0.06	0.05	0.02	0.12
2020	2.27	-0.22	-0.54	0.33	2.48
2021	3.22	0.50	-1.97	2.47	2.72
Average	2.31	0.42	1.00	-0.59	1.89

Legend: Figures are annual growth rates (in percentage points).
Values for year T refer to the growth rate between years T and T-1.
Source: Authors' calculations from STATEC data.

Table 3
Services – Productivity growth and drivers (%) – 1996-2021

Year	Labour productivity	TFP	Efficiency change	Technical change	Input deepening
1996	0.65	-4.83	11.08	-15.91	5.48
1997	3.59	-2.85	5.72	-8.57	6.44
1998	7.03	4.69	5.63	-0.94	2.34
1999	9.19	3.28	0.92	2.36	5.91
2000	7.33	3.91	5.50	-1.59	3.42
2001	-0.97	-1.36	1.52	-2.88	0.38
2002	-0.25	-2.21	0.65	-2.85	1.96
2003	4.67	-0.12	-0.77	0.65	4.80
2004	5.53	0.60	1.02	-0.42	4.93
2005	3.96	1.56	0.48	1.07	2.40
2006	7.95	4.26	2.15	2.12	3.68
2007	-1.43	1.46	-0.02	1.49	-2.90
2008	-6.85	-1.56	2.24	-3.80	-5.29
2009	-1.24	-1.41	-0.09	-1.32	0.17
2010	6.78	1.84	-0.46	2.30	4.93
2011	-0.39	-0.53	0.23	-0.76	0.14
2012	0.03	-1.26	-0.09	-1.17	1.29
2013	5.25	0.59	-0.39	0.98	4.66
2014	5.61	-0.59	1.48	-2.07	6.20
2015	1.51	0.85	-0.66	1.51	0.66
2016	-1.12	1.16	2.50	-1.33	-2.28
2017	-2.08	0.68	-0.06	0.74	-2.76
2018	-0.32	-0.45	-0.44	-0.01	0.12
2019	-0.20	-0.43	0.20	-0.63	0.24
2020	3.15	0.17	-0.29	0.46	2.98
2021	3.32	0.53	-2.16	2.70	2.79
Average	2.33	0.31	1.38	-1.07	2.03

Legend: Figures are annual growth rates (in percentage points).
Values for year T refer to the growth rate between years T and T-1.
Source: Authors' calculations from STATEC data.

Table 4
Manufacturing – Productivity growth and drivers (%) – 1996-2021

Year	Labour productivity	TFP	Efficiency change	Technical change	Input deepening
1996	0.06	-0.28	0.05	-0.33	0.34
1997	5.71	3.01	0.01	3.00	2.70
1998	7.20	3.13	0.41	2.72	4.07
1999	1.94	2.31	0.00	2.31	-0.37
2000	5.16	2.02	0.00	2.03	3.14
2001	-0.60	-1.17	0.16	-1.33	0.57
2002	2.97	1.36	0.63	0.73	1.62
2003	0.33	0.88	-0.48	1.36	-0.55
2004	3.93	1.66	0.19	1.48	2.27
2005	-1.20	0.27	-0.32	0.59	-1.47
2006	4.58	-0.06	0.34	-0.39	4.64
2007	2.78	3.32	-0.43	3.75	-0.54
2008	-1.95	-3.65	0.12	-3.78	1.70
2009	-8.16	-3.91	-0.17	-3.74	-4.25
2010	17.72	8.48	0.03	8.45	9.23
2011	2.93	1.45	-0.10	1.54	1.48
2012	-1.56	-0.62	0.11	-0.74	-0.93
2013	2.13	0.40	-0.32	0.72	1.73
2014	1.04	1.33	-0.10	1.43	-0.29
2015	8.04	9.97	-0.30	10.27	-1.93
2016	4.63	3.59	-0.72	4.31	1.04
2017	1.87	0.99	-0.58	1.56	0.89
2018	0.51	1.03	-0.71	1.74	-0.52
2019	2.48	3.09	-0.86	3.95	-0.61
2020	-3.14	-2.34	-2.01	-0.33	-0.80
2021	2.53	0.30	-0.58	0.89	2.23
Average	2.38	1.41	-0.22	1.62	0.98

Legend: Figures are annual growth rates (in percentage points).
Values for year T refer to the growth rate between years T and T-1.
Source: Authors' calculations from STATEC data.

Table 5
LRD services – Productivity growth and drivers (%) – 1996-2021

Year	Labour productivity	TFP	Efficiency change	Technical change	Input deepening
1996	0.54	-4.25	12.08	-16.33	4.79
1997	4.32	-2.38	6.52	-8.90	6.70
1998	7.60	5.74	6.28	-0.54	1.86
1999	10.12	4.52	1.13	3.40	5.59
2000	8.52	4.88	6.29	-1.41	3.65
2001	-1.07	-1.03	1.63	-2.67	-0.03
2002	-0.02	-2.10	0.44	-2.54	2.08
2003	4.87	1.01	-0.41	1.42	3.86
2004	5.42	1.03	0.99	0.04	4.39
2005	4.89	2.22	0.64	1.58	2.67
2006	8.51	4.70	2.29	2.41	3.81
2007	-1.21	1.54	-0.08	1.62	-2.74
2008	-7.43	-1.48	2.27	-3.74	-5.96
2009	-2.31	-1.42	-0.49	-0.93	-0.89
2010	7.37	2.21	-0.60	2.81	5.16
2011	-0.25	-0.32	0.23	-0.55	0.07
2012	-0.39	-1.35	-0.25	-1.10	0.97
2013	5.23	1.07	-0.06	1.13	4.16
2014	4.96	0.56	1.78	-1.22	4.40
2015	-0.62	1.01	-0.59	1.59	-1.63
2016	-3.88	1.19	2.48	-1.29	-5.07
2017	-4.02	1.45	-0.10	1.55	-5.47
2018	-2.67	-0.40	-0.70	0.30	-2.27
2019	-3.30	-0.53	-0.04	-0.50	-2.77
2020	-0.30	0.28	-0.02	0.30	-0.58
2021	1.61	0.68	-1.44	2.12	0.92
Average	1.79	0.72	1.55	-0.82	1.06

Legend: Figures are annual growth rates (in percentage points).
Values for year T refer to the growth rate between years T and T-1.
Source: Authors' calculations from STATEC data.

Table 6
MHRD services – Productivity growth and drivers (%) – 1996-2021

Year	Labour productivity	TFP	Efficiency change	Technical change	Input deepening
1996	1.42	-8.77	4.27	-13.03	10.19
1997	-1.47	-5.52	0.70	-6.21	4.05
1998	2.84	-2.97	0.93	-3.90	5.81
1999	2.42	-5.73	0.03	-5.77	8.16
2000	-2.20	-3.99	-0.78	-3.22	1.79
2001	-0.17	-4.19	0.53	-4.73	4.02
2002	-2.29	-3.14	2.42	-5.57	0.85
2003	2.99	-9.62	-3.78	-5.83	12.60
2004	6.42	-2.83	1.32	-4.15	9.26
2005	-3.44	-4.12	-0.97	-3.15	0.68
2006	3.09	0.37	0.83	-0.46	2.72
2007	-3.39	0.83	0.50	0.33	-4.23
2008	-1.72	-1.90	2.28	-4.18	0.17
2009	7.37	-1.03	3.20	-4.22	8.39
2010	2.67	-0.75	0.52	-1.26	3.41
2011	-1.38	-2.00	0.23	-2.23	0.62
2012	2.88	-0.71	0.89	-1.60	3.59
2013	5.43	-2.53	-2.54	0.01	7.95
2014	9.81	-7.61	-0.27	-7.34	17.42
2015	14.25	0.41	-0.72	1.12	13.84
2016	12.92	1.56	2.94	-1.38	11.37
2017	6.06	-2.00	0.33	-2.33	8.06
2018	8.29	-0.39	0.59	-0.98	8.68
2019	9.87	-0.06	0.90	-0.96	9.94
2020	12.89	-0.08	-1.00	0.92	12.97
2021	7.54	0.29	-3.78	4.08	7.25
Average	3.97	-2.56	0.37	-2.92	6.52

Legend: Figures are annual growth rates (in percentage points).
Values for year T refer to the growth rate between years T and T-1.
Source: Authors' calculations from STATEC data.

Table 7
LRD manufacturing – Productivity growth and drivers (%) – 1996-2021

Year	Labour productivity	TFP	Efficiency change	Technical change	Input deepening
1996	4.38	1.01	0.09	0.92	3.37
1997	3.88	1.51	0.21	1.30	2.36
1998	7.61	2.54	0.70	1.84	5.07
1999	3.09	2.13	0.46	1.67	0.96
2000	1.50	0.27	0.56	-0.29	1.23
2001	-0.83	-0.65	-0.09	-0.56	-0.18
2002	5.88	2.27	0.82	1.45	3.61
2003	-2.32	-1.67	-1.48	-0.19	-0.65
2004	-0.09	0.89	0.52	0.37	-0.98
2005	4.95	1.10	-0.13	1.23	3.85
2006	0.06	0.56	0.24	0.32	-0.49
2007	2.36	4.25	-0.86	5.11	-1.89
2008	-0.23	-2.05	0.26	-2.31	1.82
2009	-2.13	-4.32	0.13	-4.45	2.19
2010	-1.08	0.70	0.14	0.56	-1.78
2011	4.00	0.30	-0.47	0.77	3.70
2012	0.15	-0.17	0.16	-0.33	0.32
2013	4.29	0.99	0.05	0.94	3.31
2014	2.12	1.25	0.70	0.55	0.87
2015	0.66	0.65	0.32	0.33	0.02
2016	4.42	2.63	0.02	2.61	1.79
2017	-4.58	0.02	-0.16	0.18	-4.60
2018	0.58	1.25	-0.18	1.44	-0.68
2019	4.22	3.61	-0.66	4.27	0.61
2020	-2.17	-2.59	-0.92	-1.66	0.42
2021	-1.92	-0.13	-0.48	0.35	-1.79
Average	1.49	0.63	0.00	0.63	0.86

Legend: Figures are annual growth rates (in percentage points).
Values for year T refer to the growth rate between years T and T-1.
Source: Authors' calculations from STATEC data.

Table 8
MHRD manufacturing – Productivity growth and drivers (%) – 1996-2021

Year	Labour productivity	TFP	Efficiency change	Technical change	Input deepening
1996	-2.44	-0.97	0.11	-1.08	-1.47
1997	6.85	3.85	-0.17	4.02	3.00
1998	6.96	3.50	0.26	3.23	3.47
1999	1.25	2.44	-0.26	2.69	-1.18
2000	7.41	3.06	-0.36	3.42	4.35
2001	-0.46	-1.48	0.34	-1.82	1.02
2002	1.17	0.79	0.54	0.25	0.38
2003	2.12	2.56	0.17	2.39	-0.44
2004	6.57	2.14	-0.06	2.20	4.43
2005	-5.09	-0.21	-0.35	0.14	-4.88
2006	7.83	-0.54	0.37	-0.91	8.36
2007	3.08	2.70	-0.04	2.75	0.38
2008	-3.24	-4.83	0.08	-4.91	1.59
2009	-12.90	-3.47	-0.24	-3.23	-9.42
2010	35.18	13.43	-0.40	13.83	21.75
2011	2.27	2.14	0.13	2.01	0.13
2012	-2.60	-0.84	0.14	-0.99	-1.75
2013	0.73	0.02	-0.53	0.55	0.70
2014	0.29	1.39	-0.64	2.03	-1.10
2015	13.43	15.64	-0.68	16.32	-2.20
2016	4.75	4.15	-1.16	5.31	0.60
2017	5.68	1.59	-0.75	2.34	4.09
2018	0.47	0.96	-0.96	1.92	-0.48
2019	1.56	2.73	-1.05	3.78	-1.17
2020	-3.68	-2.30	-2.78	0.48	-1.38
2021	5.25	0.58	-0.63	1.22	4.66
Average	3.17	1.89	-0.34	2.23	1.29

Legend: Figures are annual growth rates (in percentage points).
Values for year T refer to the growth rate between years T and T-1.
Source: Authors' calculations from STATEC data.

2.2.8
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2.3
Intangible Capital and Labour Productivity Growth in Luxembourg

2.3.1
Introduction

Intangible capital is regarded as an important contributor to productivity and economic growth by economic policy institutions and researchers. It is, however, typically difficult to estimate and is only partially captured in datasets for economic analysis and official statistics. This can lead to bias in the estimates of productivity levels and growth. Thus, this contribution exploits a recently released cross-national dataset, the EUKLEMS-INTANProd, to describe the share, composition and relevance of the stock of intangible capital for Luxembourg's economy. Specifically, it focuses on the contribution of intangibles to labour productivity, and on how accounting for intangibles impacts the estimates of labour productivity growth. It builds on, and extends, the comparative analysis of labour productivity growth in Luxembourg, which appeared on last year's National Productivity Board report (CNP – *Rapport annuel 2021-2022*).

The remainder of this section presents a definition of intangible capital, and concisely reviews main developments in the scientific literature on intangibles and in their measurement in the context of national accounts.

Investment reports, and as a consequence capital stocks figures, have traditionally focused on physical assets such as buildings and machinery. Intangible assets – which comprise digital assets (software and databases), intellectual property (patents), research and development (R&D), design, new financial products, and a range of economic capabilities such as workforce training, organizational capital, and branding – are typically difficult to capture and are only partially accounted for in capital stock estimates. Corrado, Hulten, and Sichel (2005; 2009) provide a comprehensive classification of intangible assets, referred to as the CHS framework.

Table 1 lists broad categories and types of intangible assets according to the CHS framework. There, eight types of intangible assets are grouped into three main categories, respectively digitized information, innovation property, and economic competencies, which in turn represent three different types of knowledge. Digitized information reflects knowledge embedded in computer codes and databases. Innovative property includes knowledge acquired through scientific research, and general know-how embedded in artistic content and design. Economic competencies represent the value of branding and other knowledge embedded in firms' human and structure resources. The framework was first operationalized by van Ark et al. (2009) for different countries; these authors also performed the first analysis of the contribution of intangible capital to economic growth. Corrado et al. (2022) provide an in-depth survey of intangible capital based on the CHS framework and discusses implications for modern economies.

Table 1
Intangible assets in the CHS framework

Broad categories	Type of intangible assets	National account
Digitized Information	Software and databases	Included
Innovative Property	Research and development	Included
	Intellectual property	Included
	Industrial design	Not included
	New financial product	Not included
Economic Competencies	Branding	Not included
	Organisational capital	Not included
	Training	Not included

Source: Corrado, Hulten, and Sichel (2005)

A growing share of investment expenditure in intangibles has been a marking feature of advanced economies in recent decades. For example, in 1995, Luxembourg's intangible investment accounted for 11% of gross value added, equal to its tangible investment share. By 2019, the share of intangible investment in gross value added had increased to 15%, while tangible investment remained at 11%. As an example at the firm-level, Hulten (2010) shows that Microsoft's tangible assets such as plants and equipment accounted for only 3 billion US dollars in 2006, equivalent to 4% of its total assets and 1% of its market value, suggesting a large share for intangibles.

The distinction between tangible and intangible assets is relevant to productivity analysis. For instance, Corrado et al. (2021) suggest that growing shares of intangible assets lead to increased firm-level productivity dispersion, a feature also found in Luxembourg data (CNP – *Rapport annuel 2020-2021*). One potential mechanism behind the productivity dispersion is accumulation of intangible capital, as argued by Haskel and Westlake (2018), who show that intangible tends to benefit larger incumbent firms, thereby posing challenges and barrier for newcomers seeking to compete.[1] A recent trend in productivity studies is to account explicitly for intangibles to analyse their contribution to productivity growth, to identify productivity drivers, and to explain the observed slow-down in labour and total factor productivity. This amounts to modelling intangibles as a separate factor to production in growth accounting exercises or in empirical production models. For instance, Bontadini et al. (2022) found empirical evidence that organizational capital can lead to productivity gains. Corrado et al. (2023) consider databases as capital assets and estimate the productivity impact of increased use of data. Bronnenberg et al. (2022) discuss the implications of brand capital for productivity. Focusing on North-West Europe, the UK and the US, van Ark et al. (2023) show that the increase in intangibles have not fully offset the decline in tangible capital's productivity impact.

1 Haskel and Westlake (2018, 2022) show that intangibles contribute to the widening gap between industry leaders and laggards, even when regulatory frameworks are in place.

Intangible capital is typically difficult to estimate. While tangible assets are well-documented and accounted for in both firms' balance sheets and national capital stock and GDP figures, the measurement of intangibles is challenging. Intangible capital is only partially captured by existing datasets compiled for economic analysis or countries' national accounts. There, they are typically accounted for as costs (or intermediate consumptions) and, unlike investments in physical assets, are subtracted from value added. However, in light of their increasing relevance, standards for the compilation of national accounts – the System of National Accounts (SNA) – are being gradually modified to incorporate intangibles. Initially, the SNA 1993 update included software and intellectual property, which was followed by the inclusion of R&D in the SNA 2008 update. Thus, three out of the eight types of intangible assets have already been integrated into the national accounts system. Branding is poised to be included as capital assets in the forthcoming national accounts update, set to be agreed upon in 2023 and implemented from 2025.[2] The analysis in the remainder of this chapter suggests that these changes in accounting standards have the potential to affect significantly Luxembourg's productivity estimates.

This contribution exploits a state-of-the-art newly released dataset, EUKLEMS-INTANProd, to assess the role of intangibles in Luxembourg's economy, and its impact on the country's labour productivity growth in a comparative perspective. We track the share of intangible capital over total capital and describe the changes in the composition of intangibles in the country, from 1995 to 2019. We analyse the role and impact of intangibles on labour productivity and TFP growth, using a productivity decomposition from a standard growth accounting model.

The data show that the share of intangible capital is comparatively low in Luxembourg. Over the period from 1995 to 2019, intangibles' accumulation has been slower than in other advanced economies. Moreover, the composition of intangible assets has shifted, with an increase in the share of branding and organizational capital. The contribution of intangibles to labour productivity growth is also comparatively low in Luxembourg. Nonetheless, accounting for intangibles mitigates the slowdown in labour productivity growth after the great recession.

This contribution is structured as follows. Section 2 presents the data used in the analysis, namely the EUKLEMS-INTANProd dataset and intangible capital measurement. Section 3 presents descriptive statistics on the comparative evolution and composition of intangible capital in Luxembourg from 1995 to 2019. Section 4 delves into the role of intangible capital in labour productivity slowdown in a growth accounting framework.

2.3.2
The EUKLEMS-INTANProd dataset

The data used for this analysis is sourced from the EUKLEMS-INTANProd dataset. The dataset, compiled by researchers at LUISS University and released in early 2023, is publicly available and can be downloaded from https://euklems-intanprod-llee.luiss.it/.

The dataset combines growth accounting data from EUKLEMS with data on intangible assets from the INTAN-invest dataset for a large number of countries – including the 27 EU member states, the UK, the US, and Japan – over the period 1995-2020.[3] Observations are at yearly frequency and at industry level (42 industries according to NACE Rev. 2 classification) and for 15 aggregates. This new dataset provides opportunities to investigate the roles of intangible assets, particularly in relation to productivity.

The EUKLEMS-INTANProd dataset operationalises the classification of intangible assets proposed in the CHS framework. Bontadini et al. (2023) detail methodology and data sources used for compiling the dataset.

The EUKLEMS-INTANProd dataset includes a statistical module and an analytical module. The statistical module provides standard national accounts indicators, such as value added, gross output, intermediate expenditures, measures of labour input (employment and hours), gross fixed capital formation, stock of capital, share of employment, and labour compensation by type of workers. This module also provides information on certain characteristics of workers (gender, age, educational attainment) and estimates of "quality" of the labour input based on these characteristics. Note that capital stock here includes standard physical capital asset, but also three types of intangibles now included in national accounts, specifically computer software and databases, research and development, and intellectual property assets (compiled according to the ESA 2010 standards).[4]

The analytical module consists of series on investments and stocks of intangibles not included in the statistical module. There are the following five types of intangibles: industrial design; branding; organisational capital; training; new product development in financial industries. Series also include price deflators for the five assets, and both the nominal and real value of investments. Intangible capital stocks are derived using the Perpetual Inventory Method (PIM).

2 UNSTATS -Towards the 2025 SNA: https://unstats.un.org/unsd/nationalaccount/towards2025.asp

3 The INTAN-Invest (http://www.intaninvest.net/) is an early project dedicated to measurement of intangible assets. It provides standardized data on intangible investment for 15 EU countries and the U.S. since 1995. The more recent EUKLEMS & INTANProd combines the EUKLEMS database with updated estimates of intangible investment from INTAN-Invest project.

4 The European system of national and regional accounts (ESA 2010) defines capital stock as comprised of computer hardware; communications equipment; dwellings; other buildings and structures; transport equipment; other machinery and equipment; cultivated biological resources; research and development; computer software and databases, and intellectual property (https://ec.europa.eu/eurostat/web/esa-2010).

To compute investment flows in intangible assets, Bontadini et al. (2023) follow the same approach adopted for measuring computer software and databases in official statistics. This approach consists of estimating the "own-account" and "purchased" investments. The "own-account" estimation is based on approximating the investment cost in the asset by the cost of the personnel devoted to the production of that asset. Here, data on employment and labour compensation by type of occupation and by industry are drawn from the Labour Force Survey and the Structure Earning Survey for the EU. The "purchase" component estimates are based on intermediate costs gathered from supply-use tables. Investment in a given intangible asset is the sum of the estimates based on the two approaches, "own-account" and "purchased" estimates. As an example, firms can invest in databases via two channels. First, firms can create their own databases by reallocating or hiring workforce devoted to data creation (e.g., data managers, survey workers). This corresponds to the "own-account" case. Second, firms can purchase commercially available data from a third party. The latter is the "purchased" investment. (For more details on the "own-account" and "purchased" compilation approaches, see Bontadini et al.,2023, pp. 23-27.)

This analysis divides the sample into three periods: those before (1996-2007), during and after (2011-2019) the financial crisis of 2008-2010. We exclude the latest available year 2020. The analysis focuses on a selected number of countries: it comprises Luxembourg's neighbours, namely Germany, France, and Belgium, as well as the United States and the United Kingdom. Additionally, it includes three small European economies: the Netherlands, Austria, and Finland. All country-level figures refer to the non-agricultural business economy.[5] The term "intangible capital" denotes the aggregate stock of intangible capital, that is, the sum of all eight categories of intangible assets as listed in Table 1.[6]

2.3.3
Intangible capital in Luxembourg

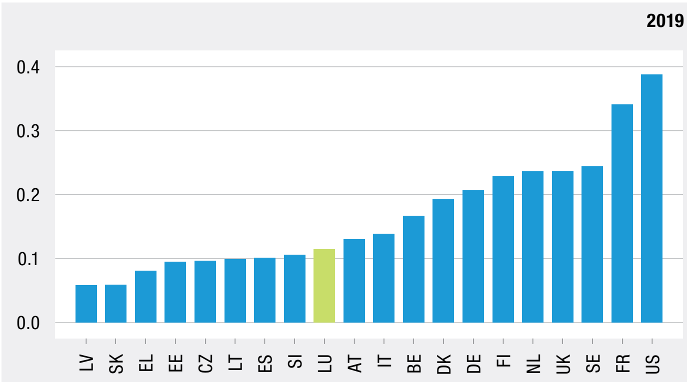
This section presents the comparative evolution of intangible capital in Luxembourg from 1995 to 2019. Specifically, we contrast the evolution of tangible and intangible capital stocks, and illustrate (changes in) the composition of the intangible stock both at the aggregate level and for selected industries. Over the period, investments in tangible assets have been outpacing those in intangibles. What is more, following the great recession of 2008-2010, investment spending into new financial products and R&D has been declining, while it has increased in branding and organisational capital, which has resulted in a considerable change in the composition of the country's stock of intangibles. Overall, Luxembourg has a comparatively small share of intangibles.

2.3.3.1
The evolution of intangible capital

Figure 1 shows the share of intangibles in total capital in 2019 for all countries available in the dataset. One can see that the share of intangibles for Luxembourg is relatively small, at 11%. It is smaller than in its neighbouring countries, i.e., Germany, France, and Belgium. For comparison, the US and France, which are leading the ranking, have more than 30% share of intangibles over total capital stock. Figure 2 compares the economies' shares of intangibles before (1996-2007) and after (2011-2019) the great recession of 2008-2010. Luxembourg sees a decline in the intangibles share.[7]

Figure 3 depicts trends of intangible (red line) and tangible (yellow line) capital for the non-agricultural business economy in Luxembourg and selected countries compared to the 1995 benchmark.[8] One sees that the accumulation of intangibles has been more sustained than the accumulation of tangible capital in all countries but Luxembourg. In contrast, Luxembourg exhibits a steady and sustained rate of accumulation of tangible capital stock. Intangible accumulation has been characterised by high volatility and wide variations over the period. Nonetheless, the periods 1995-2001 and 2014-2019 have seen a steep growth of intangible assets.

Figure 1
Share of intangible over total capital across countries (2019)



Note: Bars represent share of intangibles over total capital stock. Share values range from 0 to 1.
Source: Authors' computations on the EUKLEMS-INTANProd dataset

[5] The non-agricultural business economy includes all industries except agriculture (A), real estate activities (L), public administration and defense (O), education (P), human health and social work activities (Q), activities of households (T), and activities of extraterritorial organisations and bodies (U).

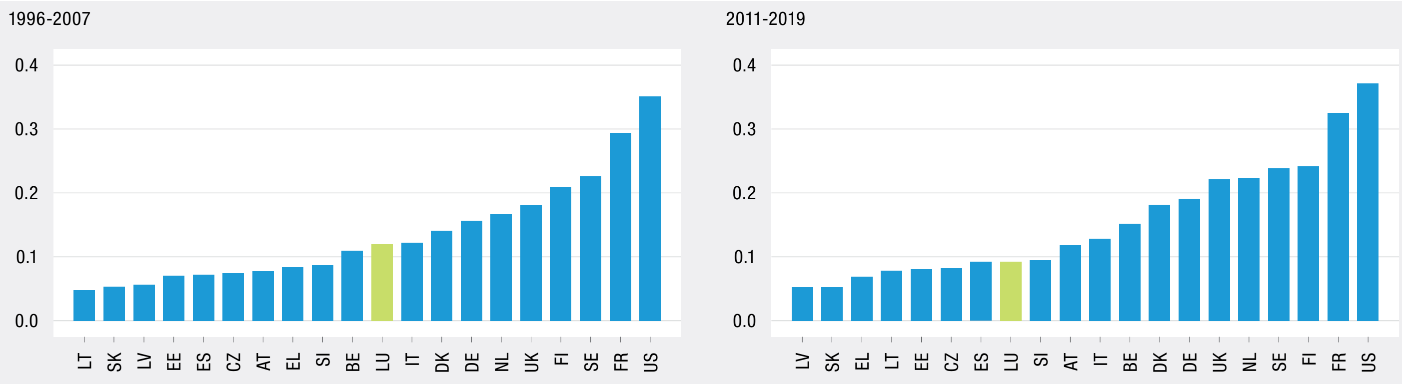
[6] Figures on Intangible assets (capital or investment flows) can be expressed in the current, previous-year prices and chain-linked volumes (with base year 2015). Investment flow refers to the annual addition of new intangible assets. Capital stock represents the accumulated assets of an economy.

[7] Note, however, that a decline in the intangibles share does not necessarily imply a decline of investment in intangibles in Luxembourg, as it could result from either a decrease in intangible investment or an increase in tangible investment.

[8] The volumes of tangible and intangible capital stock are normalized to one in 1995. As an example, in 2019, Luxembourg's stock of intangible capital is 2.5 times larger than its level in 1995.

Figure 2

Average intangible share before and after the financial crisis of 2008-2010



Note: Bars represent share of intangibles over total capital stock. The average share excludes 1995 because the observation in 1995 is missing for some countries.
Source: Authors' computations on the EUKLEMS-INTANProd dataset

Figure 3

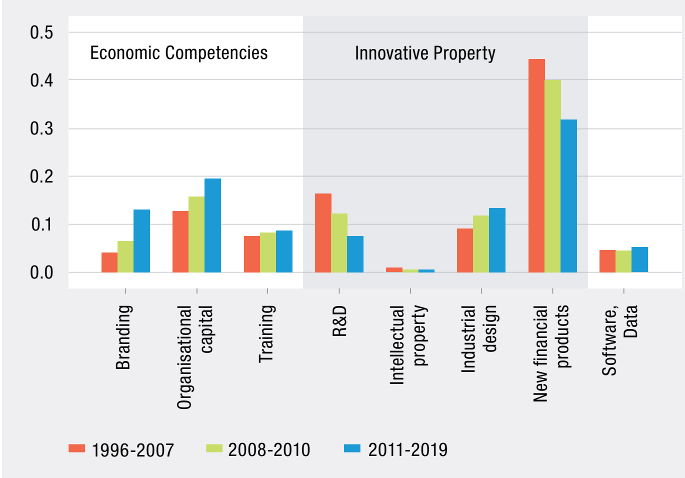
Accumulation of tangible and intangible capital (1995-2019)

Note: Trends of tangible and intangible capital (volumes – benchmark year = 1995).
Source: Authors' computations on the EUKLEMS-INTANProd dataset

2.3.3.2 The composition of intangible capital

Figures 4 and 5 illustrate changes in the composition of intangible capital in Luxembourg by type of assets and by country. The red, green and blue bars represent, respectively, average shares of intangibles for the periods 1996-2007, 2008-2010, and 2011-2019.[9] One can see that, among broad categories of intangibles, innovative property has the highest share in Luxembourg, a feature shared also by other advanced economies, with a few exceptions (Figure 5). Another notable feature, which seems to characterise solely Luxembourg and to some extent the UK, is that economic competencies have experienced a significant expansion over the period, while innovative property declined (Figure 5). New financial products are the dominant type of intangible capital in Luxembourg (Figure 4). However, their share experienced a significant decline after the recession, from about 45% before the onset of the financial crisis to about 30% in the most recent period. The share of R&D capital also declined markedly following the crisis. The share of branding, organizational capital, and industrial design has increased, while the digital capital share has remained largely stable throughout the period. In contrast, digital assets show at least some increase for other economies.[10]

Figure 4
Changes in composition of intangible capital stock in Luxembourg



Note: Bars represent average sub-period shares by type of intangible asset.
Source: Authors' computations on the EUKLEMS-INTANProd dataset

Figures 6 and 7 present the composition of intangible capital by asset type and by broad category of assets for selected service industries. (For reasons of space, we restrict attention to two periods pre- and post-recession.) As said above, Luxembourg's share of innovative property declined, while economic competencies increased. These changes in composition are associated, respectively, with an increase in branding and organisational capital, and, to a lesser extent, training, a decrease in new financial products and R&D activities. Figures 6 and 7 illustrate the composition of the intangible capital stock for two important service industries, namely the financial industries (NACE section K), and professional activities (NACE section M). These sectors are not only illustrative examples but also hold particular importance in the context of Luxembourg. The industry of financial services (K) represents the largest contributor to value added in the country.

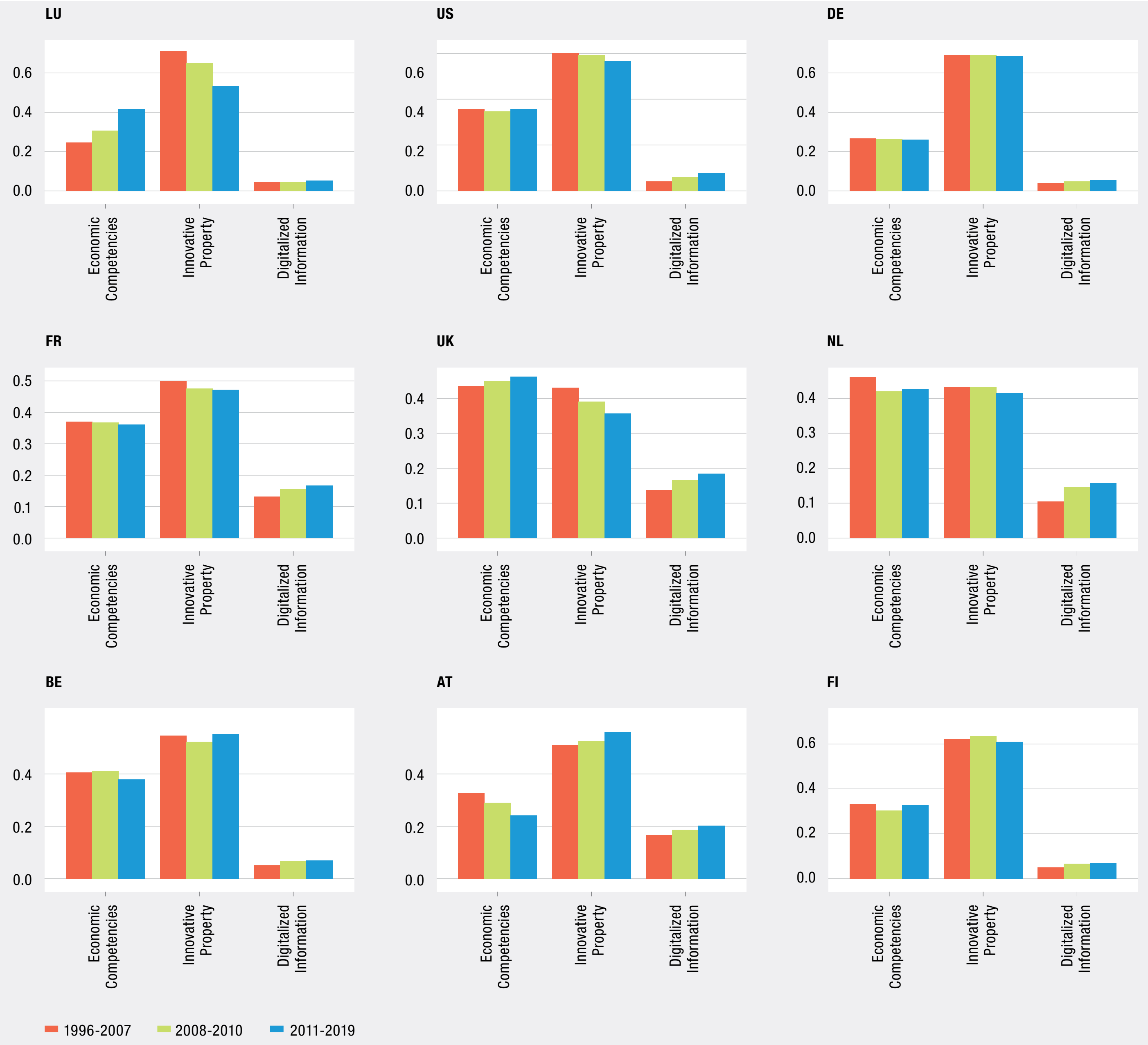
The industry of professional activities (M) has the highest share of intangible investment in its value added. These figures show that, firstly, the composition of the intangible stock varies across industry: for example, shares of R&D and design are negligible for the financial industry. Changes in the composition of intangibles in financial industries are mainly due to shifts across broad categories, with a large decrease in innovative property accompanied by the increase in organisational capital. Within categories, the composition of intangibles is stable. Professional activities saw also a large fall in innovative property assets, associated to a large decline in R&D activities, and an increase in economic competencies, mainly due to branding.

[9] Note that the average share excludes 1995 because the observations in 1995 are missing for the detailed composition breakdown.

[10] The software investment data used in the current study should include both purchased and self-developed software. However, analysts at NATIXIS (http://onala.free.fr/flas21475.pdf) have raised concerns regarding the consistency in the manner that purchased and self-developed software are included in national accounts across countries. For example, they highlight that France exhibits a high level of software investment when compared with Germany (we found a similar pattern in Figure 5), which may be due to methodological differences in accounting for this item. Additional research is needed to examine possible accounting disparities across countries. Therefore, the interpretation of international comparison of software investments should be taken cautiously.

Figure 5

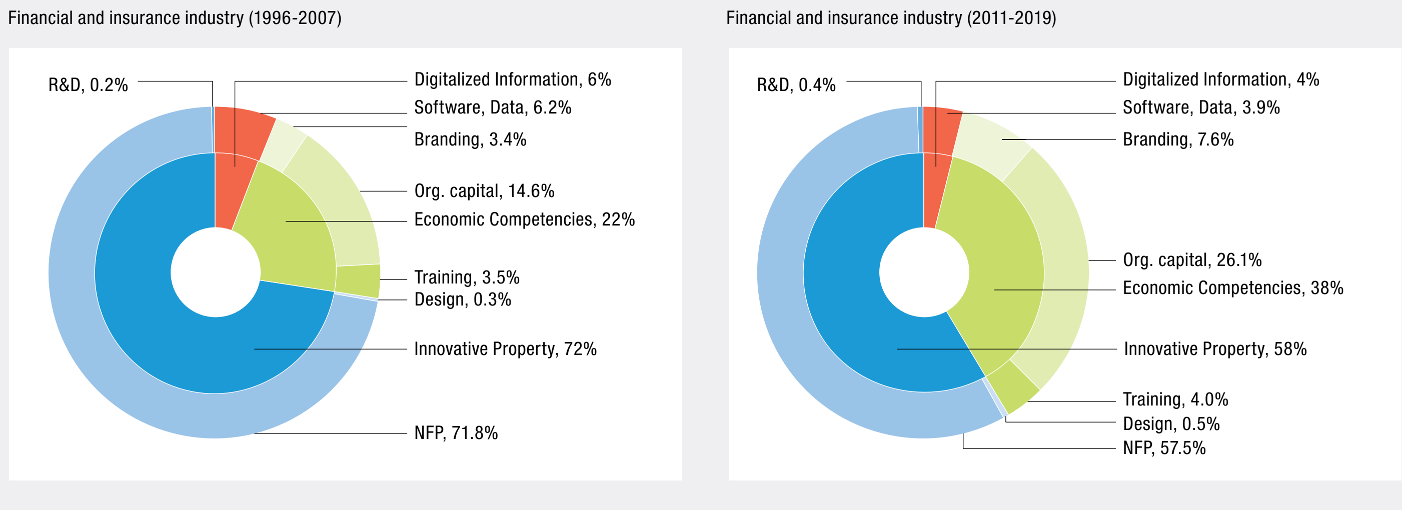
Changes in composition of intangible capital stock across countries (non-agricultural business economy)



Note: Bars are average sub-period shares by category of intangibles.
Source: Authors' computations on the EUKLEMS-INTANProd dataset

Figure 6

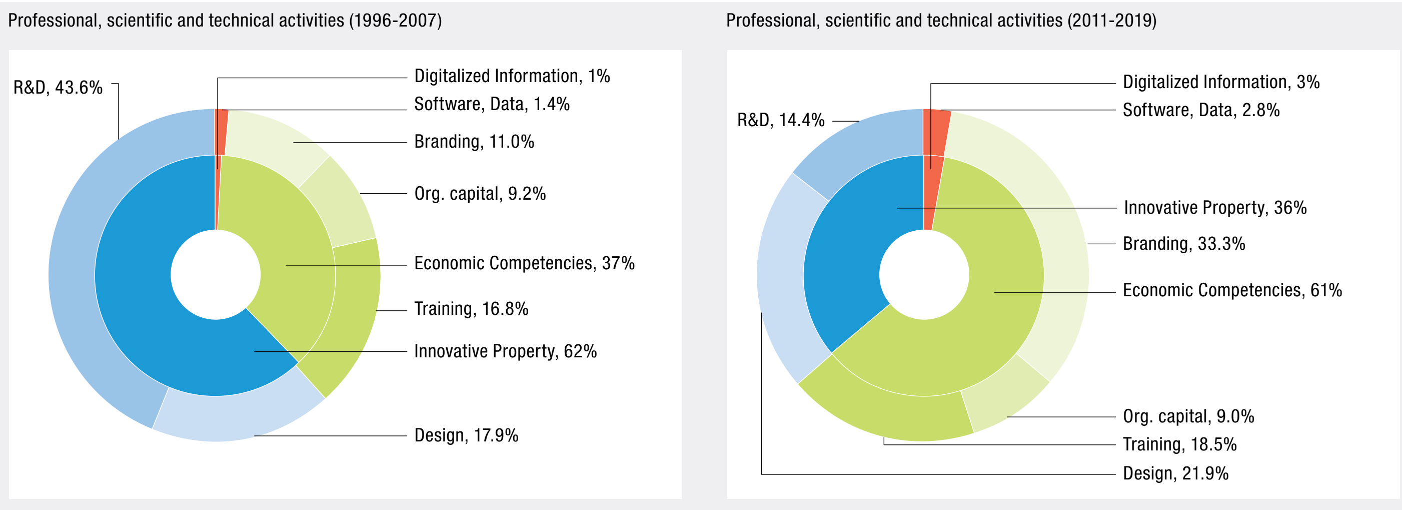
Composition of intangibles by asset type and changes – Financial and insurance industry (K) in Luxembourg



Note: Shares are period averages before and after the financial crisis. The inner circle presents the share of border categories and the outer circle displays the detailed intangible breakdown.
Source: Authors' computations on the EUKLEMS-INTANProd dataset

Figure 7

Composition of intangibles by asset type and changes – Professional, scientific and technical activities (M) in Luxembourg



Note: Shares are period averages before and after the financial crisis. The inner circle presents the share of border categories and the outer circle displays the detailed intangible breakdown.
Source: Authors' computations on the EUKLEMS-INTANProd dataset

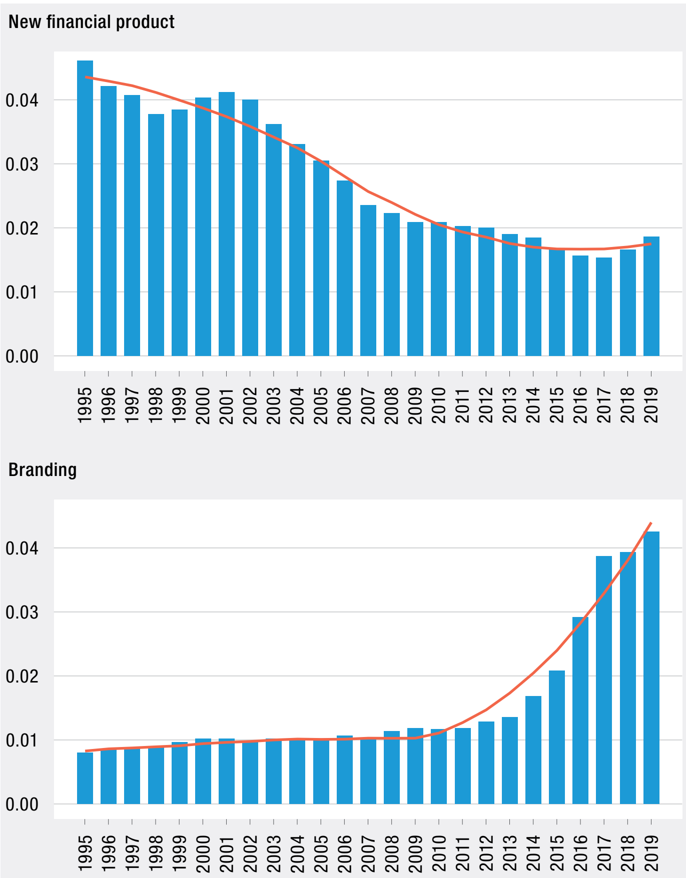
In summary, data show a decline in the share of new financial products and an increase in the share of branding assets for Luxembourg. This is mirrored by investment flows. To gain further insights, we examine investment flows in new financial product development and branding, as these flows explicitly represent the net changes in capital assets over the years.

Figure 8 depicts the investment share of aggregate value added in branding and new financial products for Luxembourg's non-agricultural business economy. In 1995, investment in new financial products in Luxembourg accounted for 4.5% of aggregate value added, while investment in branding was less than 1%. After 25 years, investment in financial products has dropped below the two percent of Luxembourg's value added, while investment in branding has exceeded 4% in 2019.

These developments might have significant implications for Luxembourg economic accounts, in light of the revised System of National Accounts (SNA) coming into force in 2025. Under the new system, branding assets will likely be officially accounted for as investment, thus affecting GDP and growth accounting computations.

Taking into account intangible assets alters the measures of both output and inputs, thereby affecting GDP and productivity growth. The following sections explore the implications of incorporating an extended range of intangible assets on productivity growth and its decomposition. Firstly, we compare the adjusted productivity growth rates, which account for all eight categories of intangible assets, with the conventional growth rates that include only those assets recognized in the current System of National Accounts – namely, R&D, software, and intellectual property. Secondly, we perform a decomposition of both standard and adjusted labour productivity growth to examine the contributions of intangible assets.

Figure 8
Yearly evolution of investment intensity in new financial product and branding (1995-2019)



Note: Bars represent the ratio of annual volumes of investment in new financial product and branding over gross value added. The red line is smoothing lines of annual ratios.
Source: Authors' computations on the EUKLEMS-INTANProd dataset

2.3.4 Labour productivity and intangible capital

This section examines the role of intangible capital in labour productivity growth within a standard growth accounting framework. Here, labour productivity is defined as the ratio of value added to hours worked. What follows compares two sets of accounts. The first one includes in value added and capital stock computations a basic set of intangibles, namely R&D, intellectual property, software and database. The second one accounts for additional intangible assets: industrial design, branding, organisational capital, training, and new product development in financial industries. The inclusion of the augmented set of intangibles changes both levels and growth rates of gross value added, as certain expenditures that were previously classified as intermediate consumption are now considered as capital goods. As a result, level and growth rates of labour productivity change.

Corrado et al. (2022, pp. 16-17) offer an in-depth analysis of the implications of incorporating intangibles into GDP and growth accounting. Including intangibles as capital assets not only increases the quantities of both output and inputs, but also the role of capital in production. In what follows, the measure based on the augmented set of intangibles will be referred to as "adjusted labour productivity". Note that we focus on the non-agricultural business economy in Luxembourg and selected countries.

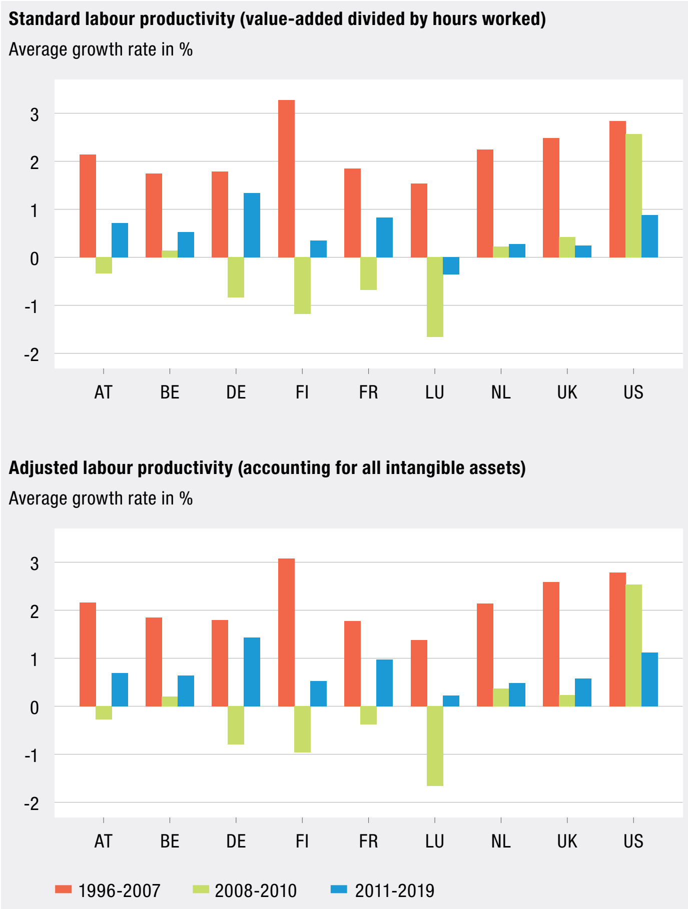
Figure 9 compares observed yearly rates of growth of standard (blue bars) and adjusted (orange bars) labour productivity for the period 1996-2019. One observes the marked fall of labour productivity in correspondence to the financial crisis, followed by a period of weaker growth and high volatility. One can see that, after the crisis, the adjusted measure of labour productivity displays consistently higher positive and less negative rates compared to the standard one.

Figure 9
Yearly growth rates of standard and adjusted labour productivity in Luxembourg

Note: Bars are yearly growth rates of labour productivity.
Lines are smoothing lines of annual growth rates.
Source: Authors' computations on the EUKLEMS-INTANProd dataset

The smoothing lines of growth rates suggest that, after the great recession, the dynamics of the two measures diverge: adjusted productivity exhibits an upward trend, while standard labour productivity shows a downward trend.[11] Overall, the figures suggest that viewing spending in intangible goods as an investment, rather than an intermediate cost, results in higher labour productivity growth. This is plausible and supports the view that intangible capital stock plays a role in enhancing productivity. In other words, this points to an underestimation of labour productivity growth when certain capital assets are omitted from the analysis.

Figure 10
Average growth rates of standard and adjusted labour productivity



Note: Bars are the period averages of labour productivity growth.
Source: Authors' computations on the EUKLEMS-INTANProd dataset

To see how this compares internationally, Figure 10 presents average standard (upper panel) and adjusted (lower panel) labour productivity growth for selected countries over the three subsamples considered in this study. While before the crisis, discrepancies between standard and adjusted labour productivity are minimal, after the crisis, adjusted labour productivity growth is higher in all countries. For Luxembourg, average productivity growth seems slightly overestimated before and during, and underestimated after the crisis.

According to standard growth accounting model (Solow, 1957), labour productivity growth can be decomposed into changes in inputs to production – the stock of capital and the labour input – and Total Factor Productivity (TFP) growth:

$$\Delta LP = \Delta \ln TFP + \Delta \textit{ labour composition} + \Delta \underbrace{(\textit{Non ICT tangible} + \textit{ICT tangible} + \textit{Intangible})/\textit{labour}}_{\textit{Capital deepening}}$$

These components can be regarded as drivers of productivity, so that the decomposition helps to clarify the contribution of each factor to productivity growth. (The following box provides further details on the decomposition.) Capital deepening represents the growth in capital assets per unit of labour (or, capital intensity). Thus, capital deepening captures workers' access to newer (better) machinery and tools in production. Here, we consider three types of capital input: non-ICT tangible, ICT tangible, and intangible capital assets. Labour composition change reflects changes in labour input (measured in hours of work), but also changes in the composition of the labour force. This takes into account certain characteristics of the labour force (age, gender, and educational attainment). Thus, the labour input term intends to capture the amount of labour as well as its quality.[12] As a result, the growth of TFP measures the change in output not explained by changes in (the quality of) inputs to production. TFP growth is conceptualised as improvements in productive efficiency and technological changes. We apply this model to both sets of accounts and measures of labour productivity described above.

The adjusted labour productivity decomposition differs from the standard one for two main reasons. Firstly, adding intangible assets directly affects the figures for the capital input, as additional assets are included in its calculation. Secondly, the inclusion of new intangibles increases the level of gross value added and labour productivity, and changes their growth rate.

[11] The smoothing lines are estimated using the Locally Estimated Scatterplot Smoothing (LOESS) method. LOESS is a nonparametric technique used for smoothing a data series without imposing prior assumptions about its inherent structure. LOESS estimates a non-linear curve at each point of x-axis using its neighbouring values (the so-called span). In Figure 9, the span is set to 0.85.

[12] An underlying assumption here is that labour quality depends on age and gender of workers. This assumption is used throughout the construction of the EUKLEMS dataset, Koszerek et al. (2007).

Box
Growth accounting

The traditional growth accounting framework (Solow, 1957) assumes that production is modelled by a function $F(.)$, which relates output to inputs used in producing that output:

$$Y = AF\,(K^*, L^*) \tag{1}$$

Y denotes the value added. K^* and L^* denote, respectively, the service of capital and labour. A represents the production technology. Input service measures the effective flow of inputs to the production process. The number of total hours worked is generally a reasonable proxy for labour service. The volume of total capital stock is considered as a proxy for capital service. This standard framework assumes that different types of capital and labour have the same marginal productivity. In the real world, firms rarely use only one type of labour or capital input. This study analyses the contribution of different types of capital assets in driving labour productivity growth. Therefore, we need to consider differences in the composition of inputs, using a weighted measure for input service.

Labour service is a Törnqvist volume index (weighted sum of log volume) of various types of workers (by gender, age and education):

$$\ln L^* = \Sigma_l \upsilon_l \ln L_l \tag{2}$$

where L_l is hours worked by worker type l; υ_l is the contribution of worker type l to the labour service with $\sum_l \upsilon_l = 1$. Capital service is a Törnqvist volume index of various types of assets (such as building, software…):

$$\ln K^* = \Sigma_j \omega_j \ln K_j \tag{3}$$

where K_j is the capital stock (chained-linked volumes) of asset type j; ω_j is the contribution of asset type j to the capital service with $\sum_j \omega_j = 1$. We assume that the production function $F(.)$ has a Cobb-Douglas form with constant return-to-scale. Thus, taking log first difference of equation (1) with (2) and (3), the growth rate of value added can be written as:

$$\Delta \ln Y = \Delta \ln A + \alpha \Sigma_j \omega_j \Delta \ln K_j + (1 - \alpha)\, \Sigma_l \upsilon_l \Delta \ln L_l \tag{4}$$

where Δ denotes the first-difference transformation; α represents the nominal share of income that goes to capital. Equation (4) can be rearranged to provide the basic growth accounting decomposition of labour productivity growth:

$$\begin{aligned} \underbrace{\Delta \ln Y - \Delta \ln L}_{\Delta LP} &= \Delta \ln A + \alpha \sum_j \omega_j \Delta \ln K_j + (1 - \alpha) \sum_l \upsilon_l \Delta \ln L_l - \Delta \ln L \\ &= \underbrace{\Delta \ln A}_{\Delta \ln TFP} + \sum_j \underbrace{\alpha\, \omega_j\, (\Delta \ln K_j - \Delta \ln L)}_{\text{contribution of capital deepening of asset } j} + \underbrace{(1 - \alpha) \sum_l \upsilon_l\, (\Delta \ln L_l - \Delta \ln L)}_{\text{contribution of } \Delta \text{ labour composition}} \end{aligned} \tag{5}$$

TFP growth ($\Delta \ln A$) measures the rate of changes in technology that affect all factors (capital and labour) proportionally. Capital deepening ($\Delta \ln K_j - \Delta \ln L$) measures changes in the capital endowment of asset type j for each unit of labour. ($\Delta \ln L_l - \Delta \ln L$) measures changes in share of hours worked by worker type l in total hours worked. The weighted sum $\sum_l \upsilon_l$ ($\Delta \ln L_l - \Delta \ln L$) measures overall changes in labour composition.

Figure 11
Labour productivity decomposition across countries (2011-2019)

Note: Black dots indicate the average of the yearly growth rates of labour productivity for the period 2011-2019. The coloured bars represent the contribution to productivity growth of the components of labour productivity: labour input (blue), tangible (green for ICT and purple for physical capital) and intangible (red) capital stock, and TFP (orange).
Source: Authors' computations on the EUKLEMS-INTANProd dataset

Figure 11 compares standard (upper panel) and adjusted labour productivity decomposition (lower panel) for the non-agricultural business economy in Luxembourg and selected countries for the period 2011-2019. (The decomposition is presented only for the period 2011-2019 for reasons of data availability. Information on labour composition is unavailable for the entire period of analysis.) The black dots denote the average rate of growth of labour productivity. The coloured bars represent the contribution of the various inputs to production and TFP to labour productivity growth. One can see that, in Luxembourg, negative average labour productivity growth is associated to negative TFP growth (upper panel). This is also apparent in a comparative perspective.

When additional intangible assets (red bars) are considered, however, the contribution of TFP is less negative, and average growth in labour productivity turns positive, albeit weak (lower panel).[13] When comparing the contribution of intangible capital deepening across countries, we observe that the contribution of intangibles to labour productivity growth is comparatively small in Luxembourg. In contrast, the contribution of tangible assets to labour productivity growth is comparatively large in Luxembourg.

In summary, our decomposition analysis confirms previous findings that the sluggish labour productivity growth in Luxembourg is closely linked to weak or even negative TFP growth. When we include a broader range of intangibles, the relative contribution of TFP diminishes, while intangibles assume a more prominent role in driving productivity growth. This analysis also shows that, compared to other countries, the contribution of intangible capital deepening to labour productivity growth in Luxembourg remains relatively modest.

Figure 12 presents the evolution over time of the contribution of intangible capital deepening (as illustrated in equation 5 of the box above) to labour productivity growth for selected countries. The calculation of these contributions is reported in the Appendix. One can see that patterns vary across countries. The contribution of intangibles remained relatively stable in the US, Belgium, and Austria over the years. In contrast, Germany, the UK, and the Netherlands witnessed significant fluctuations. France consistently saw a growing contribution of intangibles, while Finland experienced the opposite trend.

In the case of Luxembourg, we observe three periods marked by different trends. The first period, from 1996 to 2001, is characterized by relatively low but positive contributions of intangibles to labour productivity growth. This is followed by a period marked by negative contributions, from 2002 to 2015. Finally, from 2016 to 2019, the contribution of intangibles to productivity growth is positive and increasing. (This is in line with the dynamics of intangible accumulation shown in Figure 3.) In particular, Luxembourg experienced a significant increase in the contribution of intangibles to productivity in the last four years of the analysis. This coincides with the observed surge of investments in branding and market research activities between 2016 and 2019 (see Figure 8). This finding suggests that the growing investment in intangibles, particularly in economic competencies, such as branding, organizational capital, and training, is emerging as a new driver of labour productivity growth in Luxembourg.

13 The inclusion of a wider set of intangibles increases the aggregate contributions of intangibles and reduces the contribution of TFP contribution for accounting reasons. This change is because TFP was previously capturing the contributions of intangible assets; see Appendix for a detailed discussion on this point.

Figure 12
Contribution of intangibles to labour productivity growth over time

Note: Bars represent annual contribution of intangible capital deepening to labour productivity growth. Red lines are the smoothing lines of annual contributions. 1995 is missing from this figure due to the calculation of growth rates.
Source: Authors' computations on the EUKLEMS-INTANProd dataset

2.3.5
Conclusions

This contribution explored a newly released cross-national dataset, EUKLEMS-INTANProd, to describe the stock of intangible capital and its contribution to labour productivity growth in Luxembourg in a comparative perspective.

The data shows that the share of intangibles on total capital is comparatively low in Luxembourg. Over the period 1995-2019, the accumulation of intangible capital occurred at a slower pace than the accumulation of physical assets, also in comparison to other advanced economies. Intangibles accumulation featured two periods of high growth (1995-2001 and 2014-2019), and a long stagnation (2002-2013). The analysis also shows that Luxembourg's industries employ different mixes of intangible assets. What is more, the composition of intangible capital has changed over the period: the share of new financial products has declined, in face of a significant increase in branding and organisational capital.

The analysis reveals that accounting for intangible assets mitigates the productivity slowdown experienced by Luxembourg after the financial crisis. The analysis of productivity drivers shows that, while the average contribution of intangible assets to labour productivity growth is comparatively small in Luxembourg, recent trends indicate a rising importance of this type of capital. This suggests that intangible assets play an increasing role in driving productivity growth in the country. This implies that there exists potential for enhancing labour productivity growth in Luxembourg's economy through investments in intangible assets.

This contribution represents a first step in understanding the role and significance of intangible assets in Luxembourg's economy. Notably, the update to the System of National Accounts (SNA), scheduled for implementation in 2025, will officially include branding as a capital asset. In light of our analysis, this is likely to affect Luxembourg's GDP and productivity growth.

2.3.6
Appendix

In a typical growth accounting model, some variables can be directly taken from data, and others are estimated. For an industry in a given year, labour productivity (*LP*) is computed as the chain-linked volume of value added divided by the number of total hours worked (*L*). The chain-linked volume (stocks) of different capital assets K_j and hours worked by a type of L_l are available in the EUKLEMS-INTANProd dataset. The elements that are not directly observable (but can be estimated) are (i) α, the nominal share of income that goes to capital; (ii) ω_j contributions of different types of assets to capital service; (iii) υ_l contributions of different types of workers to labour service and (iv) TFP.

Calculating nominal share of capital income α

Following EUKLEMS approach, the nominal share of capital income α is estimated as the Divisia share of capital cost in value added. For industry *i* in year *t*, the Divisia index of nominal capital cost share is:

$$\alpha = \frac{1}{2}\left[\frac{\text{total capital compensation at } t}{\text{value added (in current prices) at } t} + \frac{\text{total capital compensation at } t-1}{\text{value added (in current prices) at } t-1}\right]$$

where both capital compensation and value added are expressed in current prices. Note that capital compensation equals value added at current prices minus labour compensation at current prices (data coming from Table “National account” in EUKLEMS-INTANProd dataset). Thus, we guarantee here that technology exhibits a constant return to scale.

Calculating contribution of asset type *j* to total capital service ω_j

The contribution of asset type *j* to total capital service ω_j is estimated as the Divisia share of various asset types in total capital compensation. For industry *i* in year *t*, the Divisia index of asset type *j* is:

$$\omega_j = \frac{1}{2}\left[\frac{\text{compensation of type } j \text{ at } t}{\text{total capital compensation at } t} + \frac{\text{compensation of type } j \text{ at } t-1}{\text{total capital compensation at } t-1}\right]$$

This equation satisfies the condition that $\sum_j \omega_j$, by definition, equals one. The EUKLEMS-INTANProd dataset covers 15 different types of capital:

- Computer hardware
- Communications equipment
- Dwellings
- Other buildings and structures
- Transport equipment
- Other machinery and equipment
- Cultivated biological resources
- Research and development
- Computer software and databases
- Intellectual property
- Industrial design
- Branding
- Organisational capital
- Training
- New product development in financial industries

Note that capital compensation of a given asset type is not directly observed in data. The capital compensation is calculated as the product of the cost of using one unit of a given asset (the so-called user costs of capital) and the volume of corresponding asset. The user costs of capital are calculated by EUKLEMS.

Calculating contribution of worker type *l* to total labour service υ_j

The contribution of worker type *l* to total labour service υ_j is estimated as the Divisia share of type *l* worker in total labour compensation:

$$\upsilon_l = \frac{1}{2}\left[\frac{\text{compensation of type } l \text{ at } t}{\text{total labour compensation at } t} + \frac{\text{compensation of type } l \text{ at } t-1}{\text{total labour compensation at } t-1}\right]$$

Data for labour compensation of different types of workers can be found in Table "Labour" in EUKLEMS-INTANProd dataset. This table provides shares of employment and labour compensation by types of workers cross-classified by gender (male; female), age (15-29; 30-49; 50+) and education attainment (high; medium; low). The main source of information for this table comes from EUROSTAT’s Labour Force Survey and Structure Earning Survey (for European countries), Bureau of Labor Statistics and Industrial Productivity Studies (for the US). This table is used to estimate the quality of labour inputs with different compositions. The underlying assumption for calculating total labour service (also used in other EUKLEMS studies) is that effective labour service is proportional to the number of hours worked by different types of workers, and workers are paid according to their marginal productivity (the classic assumption: wages equals marginal productivity).

Calculating TFP

Given estimates of α, ω_j and υ_j above, TFP growth is calculated as a residual:

$$\Delta \ln TFP = \Delta LP - \text{sum of contributions of capital deepening} \\ - \text{contributions of } \Delta \text{ labour composition}$$

Note that contributions of capital deepening or labour composition change are independent on what are included in the decomposition. However, TFP term depends on the decomposition model. For instance, lack of information on labour does not affect the calculation of capital deepening, $\alpha\ \omega_j\ (\Delta \ln K_j - \Delta \ln L)$. In particular, α and ω_j can be estimated independently as showed in Appendix. K_j and L are directly taken from the data. As a residual, the calculation of TFP, however depends on whether including the labour composition term. Without accounting for labour composition, TFP is calculated as the residual that incorporates contribution of labour composition change:

$$\Delta \ln TFP' = \Delta LP - \text{sum of contributions of capital deepening}$$

2.3.7
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2.4
Management practices and labour productivity: a firm-level analysis for Luxembourg

2.4.1
Introduction

In mainstream economic literature, management practices (MPs) are considered as a relevant factor in explaining persistent productivity differentials between firms and across countries (Bloom and Van Reenen, 2010; Bloom et al., 2019). Scur et al. (2021) offer an overview of various findings from firm-level analysis based on the World Management Survey (WMS) data collection methodology and related survey tools. This overview suggests a positive relationship between MPs quality and enterprise performance, with higher MPs quality scores being associated with higher productivity, profits, growth, survival rate, and innovation. Experimental evidence also points to the presence of a causal effect from MPs to productivity that is difficult to detect in correlational studies (Scur et al., 2021; Bloom et al., 2019).[1]

The original WMS is developed around an interview-based tool covering 18 practices over four areas: operations, monitoring, targets, and incentives. Answers obtained from middle management are scored by independent interviewers on a scale from 1 to 5 based on open-ended questions. Bloom and Van Reenen (2007, pp. 1360-1366) describe in detail the WMS data collection process and the measures adopted to enhance data quality.[2] In this respect, the literature highlights that the development of systematic measures of MPs performed through the WMS is important to understand the relationship between managerial structure and organizational performance (Scur et al., 2021).[3]

Taking some initial steps in this direction, for the first time the CIS 2018 for Luxembourg includes ad hoc questions on the importance of two MPs inspired by the Management and Organizational Practices Survey 2015 (MOPS 2015). The MOPS 2015 was administered by the US Bureau of Census and took the WMS as a general starting point (Buffington et al., 2017, p. 3; Scur et al., 2021, p. 234). Following the literature, the present analysis relies on these new questions to investigate the association between MPs importance and enterprise performance expressed in terms of labour productivity. Labour productivity is measured with reference to both turnover sales (S) and value added (VA).

In addition to the relationships with enterprise performance, economic research has devoted considerable attention to the factors associated with variations in MPs across firms and countries. The main focus has been on product market competition, human capital, ownership type, labour market regulations, and enterprise multinational structure (Bloom and Van Reenen, 2007; Bloom and Van Reenen, 2010; Bloom et al., 2012a; Bloom et al., 2017; Bloom et al., 2019).

Therefore, the present research proposes also some preliminary descriptive analysis of the factors that affect variation of MPs across firms, focusing on product market competition, and human capital. Research typically shows that these two factors are positively related with management quality (e.g., Bloom and Van Reenen, 2010; Bloom et al., 2012a). Product market competition may raise MPs quality through increased managerial effort and through the exit of enterprises with relatively inferior practices (e.g., Bloom and Van Reenen, 2007; Van Reenen, 2011). In the case of human capital, typically proxied by workforce education, more educated managers may understand better the advantages of modern management practices, and more educated workers may facilitate their implementation (e.g., Bloom et al, 2012a).

Section 2.4.2 of this article briefly describes the data and available information. Section 2.4.3 provides some descriptive statistics about the MPs variables, as well as on their relationships with labour productivity and with selected factors that may influence their adoption. Section 2.4.4 extends the performance aspects of the investigation within a more formalised regression analysis. Section 2.4.5 summarises the main conclusions from the research.

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[1] See also Syverson (2011) for a review and an assessment of relevant research.

[2] Further information on the World Management Survey project can be found at https://worldmanagementsurvey.org/

[3] In their review of empirical studies, Siebers et al. (2008) suggest indeed that the mixed results obtained on the relationships between complementary MPs and productivity are mainly due to the definition, the measurement, and the level of analysis of MPs.

2.4.2
Data and available information

The analysis relies mainly on firm-level information from the Community Innovation Survey (CIS) 2018 for Luxembourg, drawing additional data on enterprise output from the Structural Business Statistics (SBS) data-set.

The CIS targets many important aspects of enterprise innovation for firms with at least 10 employees in business sectors. The CIS 2018 for Luxembourg covers the three-year period from 2016 to 2018 and collects relevant auxiliary variables that support the present research.[4]

Notably, the CIS 2018 for Luxembourg includes for the first time ad hoc questions on two MPs inspired by the Management and Organizational Practices Survey 2015 (MOPS 2015), as mentioned in the previous Section. The questions included in the CIS 2018 are reported below:

During the three years 2016 to 2018, how important to the management of your business were the following methods of organising work?

i. Periodic monitoring of performance indicators of your firm
ii. Evaluation of individual (or employee) job performance

The respondents can rate the importance of each practice as "high", "medium", "low" and "not important".[5] The questions provide information on the presence and the importance of processes for assessment of individual performance and for monitoring of production targets. The second question is inspired by the *incentive* dimension covered by MOPS/WMS methodology. However, it does not provide information about the actions taken on the basis of the performance evaluation. The first question refers instead to the *monitoring* area, with a focus on the production process but still lacking details on the use made from the information. Moreover, both questions refer to the subjective importance of the practices for the firm rather than to an assessment of the quality or the extent of their implementation, as done instead in the MOPS/WMS frameworks[6]. An additional potential limitation is that the reduced number of practices may not provide a sufficiently comprehensive view of MPs adopted within firms.

As indicators of enterprise performance, the analysis will consider labour productivity measured in terms of sales turnover and value added in 2018. To this purpose, the CIS is complemented with data on both variables from Structural Business Statistics (SBS).[7] The reason is that value added is available only from the SBS and that SBS turnover data in 2018 for some industries were revised posterior to the CIS data production. Unfortunately, the SBS coverage of financial firms is limited compared to the CIS.

This smaller SBS coverage requires therefore to rely on CIS turnover data for financial firms not present in the SBS.[8] Moreover, the value added analysis excludes financial enterprises due to the relatively limited SBS coverage for such firms.

In compliance with the relevant guidelines, turnover data from CIS do not include revenues from royalties, which are instead included in SBS value added. Royalties are therefore subtracted from value added to provide a more homogenous comparison between the two different output measures.[9]

2.4.3
Descriptive statistical analysis

This Section presents a descriptive statistical analysis of the MPs variables and their relationship with the proposed performance measures. Some descriptive statistics on their association with workforce education and product market competition are also included. The rationale for this investigation has been illustrated in Section 2.4.1, which provides references to the relevant literature.

For this descriptive analysis, the answers to the MPs questions have been recoded into two categories: a first category for "High" and "Medium" importance and a second one for "Low" and "Not important". Table 1 shows the percentage of firms in each category for the two MPs, both jointly and individually.

Table 1 shows that monitoring of performance indicators (PI) has medium or high importance for 65% of the firms, while it is perceived of little or no importance in the remaining 35%. The corresponding percentages for job performance evaluation (JP) are 62% and 38%. This indicates that the two MPs are generally perceived as important for the business.

Table 1
MPs importance: rating percentages

	Performance Indicators monitoring (PI)		
	None or little	Medium or high	Total
Job performance evaluation (JP)			
None or little	27%	11%	38%
Medium or high	8%	54%	62%
Total	35%	65%	100%

Note: The table shows the percentage of firms within each category identified by the row and column headers. Percentages are weighted using CIS 2018 sampling weights.
Source: Authors' calculations based on STATEC CIS 2018 data

4 The survey is administered through a harmonised questionnaire developed according to the guidelines of the Oslo Manual (OECD/Eurostat, 2018). Additional information on the CIS 2018 is reported in the Appendix.

5 The two MPs are included alongside three other methods of organising work and are placed at the bottom of the list.

6 It is worth mentioning that the World Bank Enterprise Surveys (Enterprise Surveys www.enterprisesurveys.org, The World Bank) collects data on MPs of Luxembourgish firms by adapting a subset of questions developed by Bloom and Van Reenen (2007). For more information, see World Bank (2023, p. 118).

7 The SBS contains firm-level information on output, employment, investments, and other relevant variables for productivity analysis. More information on the SBS dataset is in Appendix.

8 The adopted strategy is to rely on SBS turnover data for all firms and use CIS turnover when the information from SBS is missing or zero.

9 An additional reason for excluding financial firms is the presence of missing information that would prevent calculation of royalties for a subset of such firms, further reducing the potential gain from their inclusion.

Table 2
Importance ratings of PI according to JP ratings

	Performance indicators monitoring (PI)		
	None or little	Medium or high	Total
Job performance evaluation (JP)			
None or little	71%	29%	100%
Medium or high	13%	87%	100%
Total	35%	65%	100%

Note: The table shows the percentage of firms that considers PI of high or low importance for each rating level of JP. Percentages are weighted using CIS 2018 sampling weights.
Source: Authors' calculations based on STATEC CIS 2018 data

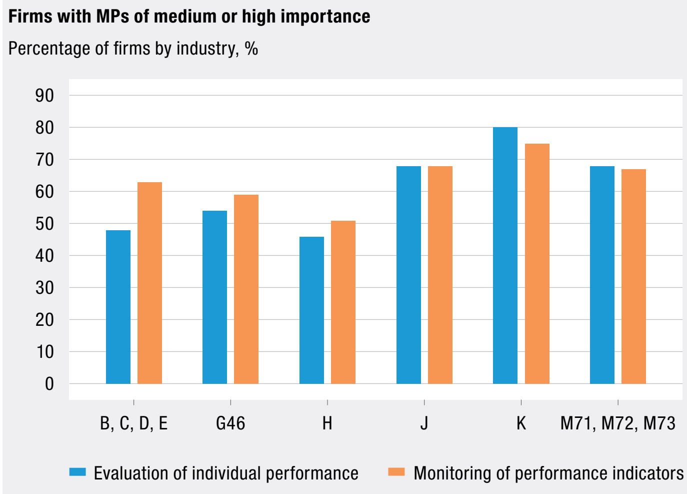
The table also shows that both practices are jointly important in 54% of the firms, while they are jointly perceived as unimportant in 27% of the firms. Therefore, 81% of the enterprises assign the same rating to both practices, while only the remaining 19% rate them differently.[10] Tables 2 explores this further by considering the importance attributed to PI for a given rating of JP.

Table 2 shows that 87% of all companies that attach medium or high importance to JP consider PI to be equally relevant, while only the remaining 13% consider the latter of little or no importance. Repeating the same exercise for JP importance conditional on the PI ratings would show that 83% of all companies that attach medium or high relevance to PI attribute equal importance to JP.

Overall, these descriptive statistics document a positive association between the importance ratings attributed by the firms to the two MPs.[11] In other words, enterprises tend to consider the two practices as jointly important for their business.[12]

Figure 1 shows the percentage of firms that consider the MPs of medium or high importance according to the industry to which they belong (NACE Rev. 2 industrial classification). Consistently with the positive association mentioned before, the two practices seem to receive similar ratings within each industry. At the same time, the data may hint to a possible greater focus on monitoring of performance indicators in Mining, Manufacturing and Utilities (Sections B, C, D and E). Financial firms (Section K) seem to attribute the highest importance to the MPs, followed closely by enterprises in Information and communication (Section J) and Professional, scientific and technical activities (Divisions M71, M72 and M73 only). The two MPs appear relatively less important for the business of the remaining industries.[13]

Figure 1
MPs importance by industry



Note: The chart shows the percentage of firms that consider the MPs of medium or high importance by industry according to the NACE Rev. 2 classification. The industries included are:
- B, C, D and E: Mining, Manufacturing and Utilities
- G46: Wholesale trade (except of motor vehicles and motorcycles)
- H: Transportation and storage
- J: Information and communication
- K: Financial and insurance activities
- M: Professional, scientific and technical activities (includes only NACE Rev. 2 Divisions M71, M72 and M73).

Please see the Appendix for more details on the definitions of the industries according to the NACE Rev. 2 classification. The statistics are weighted using CIS 2018 sampling weights and refer to the entire target population.
Source: Authors' calculations based on STATEC CIS 2018 data

The remaining part of this Section presents some descriptive statistics on the relationship between MPs and labour productivity. As mentioned in the previous Sections, labour productivity is measured in terms of both sales turnover and value added per person employed.[14] The productivity variables refer to 2018, which is the end of the period covered by the CIS. The association of MPs importance with product market competition and workforce education level is also considered.

Figure 2 shows the percentage of enterprises that consider the MPs of medium or high importance by quintiles of the distribution of persons employed (L), sales turnover (S), and labour productivity based on turnover (S/L). These statistics refer to the entire target population of the CIS 2018.

10 When the level of detail is increased by considering the four ratings separately, the percentages are still about 59% for concordant ratings and 41% for the opposite case.

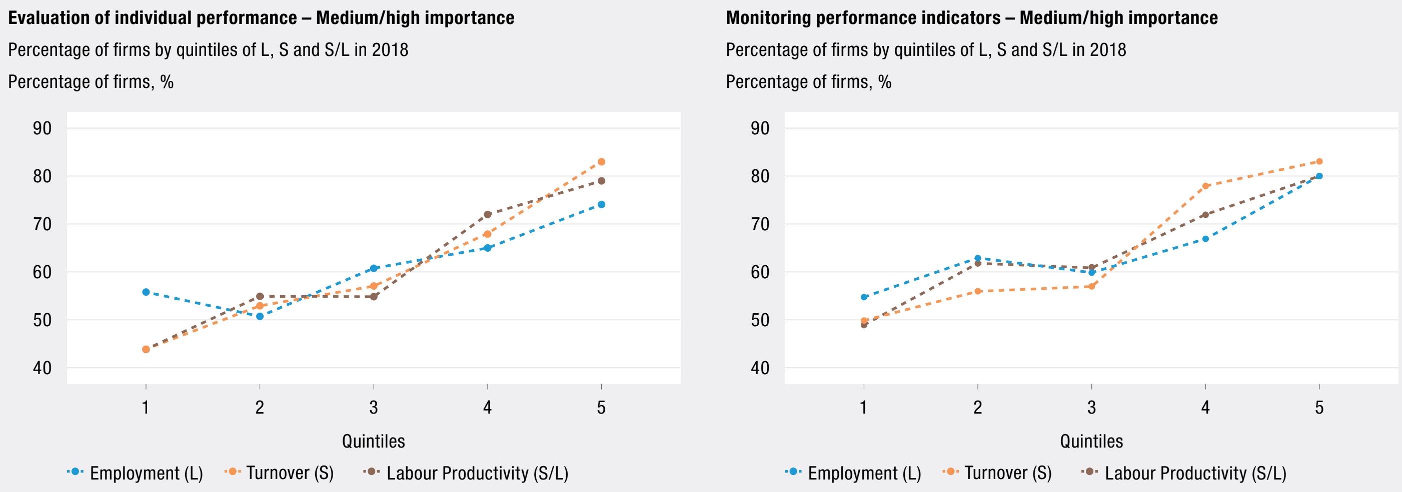
11 The Pearson x^2 test rejects the hypothesis of independence at high level of statistical significance (p-value = 0.000). The same result is obtained when considering all four ratings separately.

12 This positive association and its implications are discussed in more detail in Section 2.4.4 with references to the literature.

13 An assessment of the statistical significance of these differences would be needed to draw final conclusions.

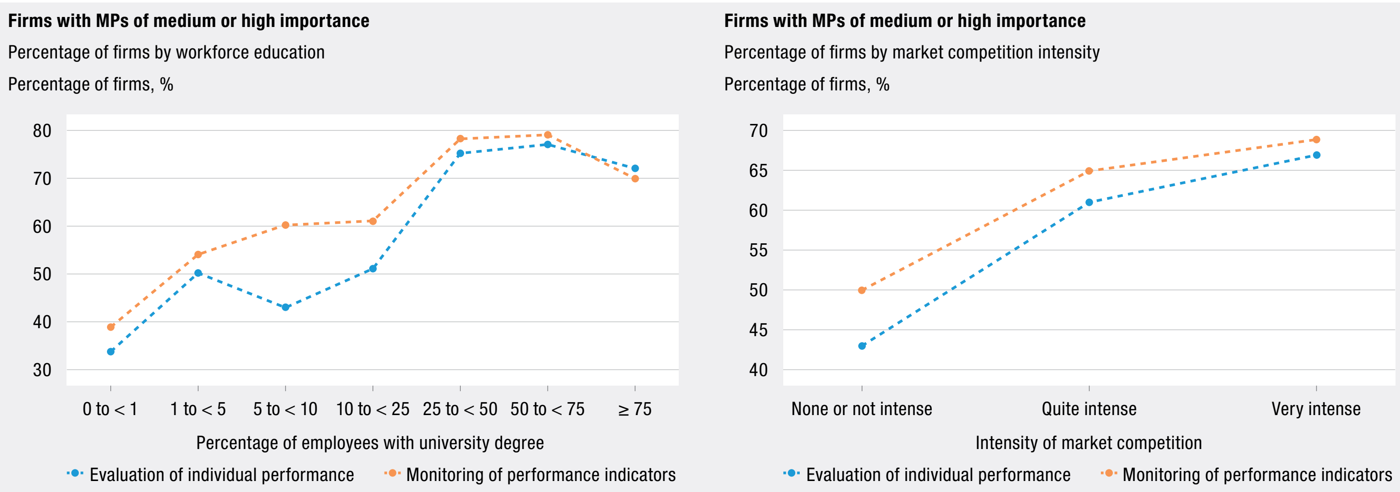
14 Both turnover and value added are expressed in volumes at the chained prices of the previous year using the respective National Accounts deflators at 2-digit level (NACE Rev. 2). Some economic activities are assigned deflators for the closest industry type.

Figure 2
MPs importance by quintiles of employment, turnover, and productivity distributions



Note: The charts show the percentage of firms that consider the MPs of medium or high importance by quintiles of the distribution of persons employed (L), sales turnover (S), and labour productivity based on turnover (S/L). Quintiles refer to the distribution of the variables expressed in logarithm and winsorised at 1% in each tail. The statistics are weighted using CIS 2018 sampling weights and refer to the entire target population.
Source: Authors' calculations based on STATEC CIS 2018 and SBS data

Figure 3
MPs importance by workforce education and market competition intensity



Note: The charts show the percentage of firms that consider the MPs of medium or high importance according to the percentage of employees with university degree (left pane) and the level of perceived competition intensity (right pane). The statistics are weighted using CIS 2018 sampling weights and refer to the entire target population.
Source: Authors' calculations based on STATEC CIS 2018 data

The charts in Figure 2 show that the percentage of firms that consider the MPs of medium or high importance tends to increase with employment, turnover, and productivity. This suggests that firms that attribute higher importance to the MPs tend to be larger and more productive. Therefore, the message from these summary statistics appears aligned with the findings from the economic literature considered in this work.[15]

Figure 3 shows the percentage of firms attributing medium or high importance to the MPs according to workforce education and market competition intensity. Workforce education is measured by the percentage of employees with university degree in 2018. This measure is coded into seven contiguous intervals shown in the left pane of Figure 3.

15 The literature also detects a positive association between employment size and management quality, which may indicate that better managed firms tend to expand more than others. For this and alternative interpretations, as well as references to the literature, see for instance Bloom and Van Reenen (2010) and Bloom et al. (2012b).

Figure 4
MPs importance by quintiles of labour productivity distributions excluding Finance

Note: The charts show the percentage of firms that consider the MPs of medium or high importance by quintiles of the labour productivity distributions based on turnover (S/L) and value added (VA/L). Quintiles refer to the distribution of the variables expressed in logarithm and winsorised at 1% in each tail. Revenues from royalties are subtracted from value added. The statistics are weighted using CIS 2018 sampling weights and exclude the financial sector (Section K).
Source: Authors' calculations based on STATEC CIS 2018 and SBS data

The CIS 2018 respondents provide also an assessment of the competition in their main market over the 2016-2018 period. The perceived intensity can be rated as "No competition", "Not very intense", "Quite intense" and "Very intense". In the analysis, the first two categories are combined due to the relatively small number of available observations.

The charts in Figure 3 show that the percentage of firms considering the MPs of medium or high importance tends to increase with perceived competition intensity and with the percentage of employees holding a university degree. This suggests that enterprises with more educated labour force and those that face stronger competition tend to attribute higher importance to the MPs. Results from these summary statistics appear therefore consistent with the findings from the reviewed literature.

Figure 4 shows the percentage of enterprises that consider the MPs of medium or high importance by quintiles of the labour productivity distributions based on sales turnover (S/L) and value added (VA/L). As mentioned previously, revenues from royalties are subtracted from VA and financial enterprises are excluded from the analysis due to limited SBS coverage.

The charts in Figure 4 show that the percentage of firms that consider the MPs of medium or high importance tends to increase with both measures of labour productivity. This again indicates that firms that attribute higher importance for their performance to the MPs tend to be more productive, in alignment with the results from the literature considered.

The descriptive statistics presented in this Section provide a preliminary assessment of the main data patterns that require confirmation through additional analysis. Nonetheless, they suggest that enterprises tend to consider the two MPs as jointly important for their business. Moreover, consistently with results from the reviewed literature, firms that attach higher importance to the MPs tend to be larger or more productive. Finally, and again in alignment with findings from the proposed literature, firms that occupy a more educated labour force or that face stronger competition tends to consider MPs as more important for their business.

2.4.4
Regression analysis

The regression analysis presented in this Section investigates the relationship between MPs importance and labour productivity taking into account other elements that may affect the latter. In addition to the variables already described in Section 2.4.3, the research considers whether the firms belong to an enterprise group, but without distinguishing between domestic or foreign.[16] In any case, it is important to clarify that the analysis does not aim to establish causality from MPs to productivity, but only the presence of a statistical correlation between the two.[17]

Following the literature on the subject, the individual MPs indicators for the econometric analysis are combined into an overall index.[18] The procedure consists in standardising each MPs variable, calculating the average between the two scores for each firm and further standardise the average to obtain a final index of MPs importance.[19]

This research considers the full CIS sample as well as a sub-sample that excludes financial firms. Therefore, the above procedure is performed separately for each sample.[20] The Pearson correlation coefficient between the two individual MPs scores in both samples is around 0.69 and statistically significant (p-value = 0.000). This reflects the positive association between the importance of the two MPs discussed in the previous Section. This positive correlation may support the interpretation of the two MPs as expression of an underlying latent variable of quality management that the index would reflect in such case.[21] However, further analysis is needed to draw sufficiently robust conclusions in this respect.

Borrowing the general idea from Bloom and Van Reenen (2010), the firm-level regression analysis is based on the following equation:

$$lp_i = \alpha + \beta_1 MP_i + \delta_1 GRP_i + \sum_j \delta_2^j EDU_{ji} + \sum_k \delta_3^k CMP_{ki} + \sum_m \delta_4^m IND_{mi} + \varepsilon_i$$

where lp_i represents the logarithm of labour productivity and MP_i the MPs importance index for firm i.[22] GRP_i, EDU_{ji}, CMP_{ki} and IND_{mi} indicate dummy variables for education level, group affiliation, competition intensity, and two-digit industry. The terms α and ε_i represent respectively the model constant and equation error term.

Table 3
Regression results

	CIS sample excluding Finance		Full CIS Sample
	VA/L	S/L	S/L
MPs score	0.07**	0.18**	0.19***
	(0.024)	*(0.020)*	*(0.008)*
Employees with university education (%)			
0% to < 1%	(base category)	(base category)	(base category)
1% to < 5%	0.06	0.15	0.09
	(0.445)	*(0.245)*	*(0.504)*
5% to < 10%	0.02	0.29	0.24
	(0.875)	*(0.277)*	*(0.414)*
10% to < 25%	0.06	0.46**	0.39*
	(0.262)	*(0.012)*	*(0.054)*
25% to < 50%	0.26**	0.34	0.40**
	(0.0101)	*(0.104)*	*(0.018)*
50% to < 75%	0.60***	0.70***	0.68***
	(0.003)	*(0.006)*	*(0.004)*
≥ 75%	0.57**	0.85*	0.78**
	(0.014)	*(0.056)*	*(0.017)*
Group affiliation			
No	(base category)	(base category)	(base category)
Yes	0.17*	0.34***	0.42***
	(0.059)	*(0.0099)*	*(0.002)*
Intensity of market competition			
None or not intense	(base category)	(base category)	(base category)
Quite intense	-0.09	0.06	0.06
	(0.224)	*(0.584)*	*(0.634)*
Very intense	-0.25**	-0.09	-0.01
	(0.022)	*(0.641)*	*(0.947)*
Industry dummies	YES	YES	YES
Number of weighted observations	~1500	~1500	~1800
Adjusted R-squared	0.35	0.40	0.42

Note: VA/L and S/L indicate labour productivity measured in terms of value added (VA) and sales turnover (S). The productivity variables are expressed in logarithm and winsorised at 1% in each tail of the distribution. Both VA and S exclude revenues from royalties. The symbols ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively. Estimates are performed by ordinary least square and are weighted using CIS 2018 sampling weights. Standard errors are clustered by NACE Rev. 2 Division. The p-values are obtained by wild bootstrapping and reported in parentheses. The number of observations in the CIS sample excluding Finance are slightly different for VA/L and S/L but rounded to the same number due to confidentiality constraints.
Source: Authors' calculations based on STATEC CIS 2018 and SBS data

16 A distinction between domestic and foreign group could be obtained by exploiting information on the head office location. However, this refinement would require additional investigation.

17 This point is often remarked in the literature. See, for instance, Bloom and Van Reenen (2007, p. 1375), Bloom and Van Reenen (2010, p. 208) and Bloom et al. (2012b, p. 612). See also Scur et al. (2021, p. 245) for a summary and for references to research based on randomized controlled trials that is meant to overcome this issue.

18 See Scur et al. (2021, p. 238).

19 Standardisation of a variable consists in subtracting its mean and dividing by its standard deviation to make it independent from the measurement scale. A detailed description of the general procedure to calculate these z-scores can be found in Bloom et al. (2012b, pp. 599-601). As this research includes only two MPs, the procedure is simplified accordingly. It is worth noticing that the availability of only two practices, each containing a relatively limited number of ratings, may somehow weaken the rationale underpinning the index.

20 For each of the two samples, the standardisation is performed with reference to the mean and the standard deviation of the corresponding target populations.

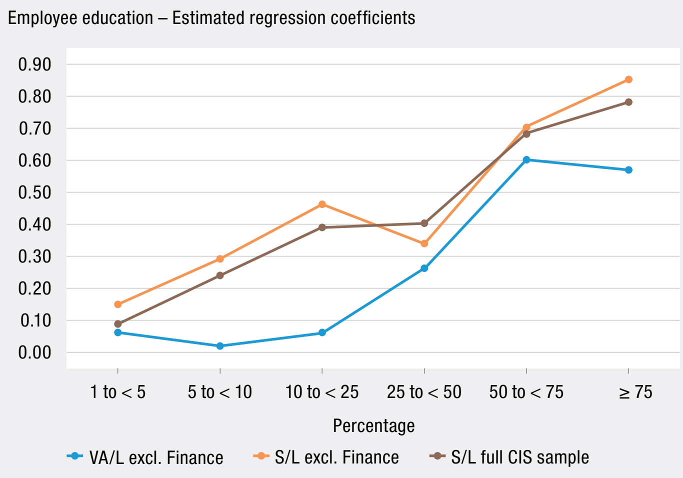
21 This may be considered as a relevant conceptual aspect. See for instance Bloom et al. (2012b, p. 601) and the references therein. As Bloom et al. (2019, p. 1656) point out with reference to Brynjolfsson and Milgrom (2013), positive correlation among practices could signal either complementarities or the presence of a common underlying driving factor.

22 Besides being expressed in logarithm, the productivity variables are winsorised at 1% in both tails of the distribution.

As already mentioned in Section 2.4.3, labour productivity is measured in terms of both value added (VA/L) and sales turnover (S/L) in 2018. Both VA and S exclude revenues from royalties. Estimates for VA/L are performed excluding the financial sector due to the limited SBS coverage. Estimates for S/L are also presented for the full CIS sample.

Table 3 shows the estimation results.[23] The coefficient on the MPs index appears positive and statistically significant at conventional levels in all estimates. For the sample without financial firms, a one standard deviation increase in the index is associated with approximately 7.3% increase in value added productivity and 19.7% in turnover productivity.[24] Based on the point estimates alone, this indicates that the association between MPs importance and productivity may be stronger in terms of turnover than in terms of value added.[25] However, further analysis would be required to assess the statistical significance of this differential. Looking at the full sample, an increase of one standard deviation in the index is associated with about a 20.9% variation in turnover productivity. Therefore, the association appears sizeable and significant regardless of the treatment of financial firms.[26] Overall, these results are qualitatively aligned with the positive association between MPs and performance typically detected by the literature reviewed in this work.

Figure 5
Percentage of employees with university education: estimated regression coefficients



Note: The chart plots the estimated regression coefficients for the percentage of employees with university education presented in Table 3.
Source: Authors' calculations based on STATEC CIS 2018 and SBS data

A high percentage of employees with a university degree appears positively and significantly associated with all types of labour productivity, suggesting a beneficial role of human capital.[27] To facilitate the reading of the results, Figure 5 presents the estimated coefficients from the three regressions. The chart shows a tendency for an almost monotonic increase in the coefficients. This suggests that, compared to the reference category of 0% to 1%, a higher percentage of employees holding a degree is associated with higher labour productivity. As shown in Table 3, this association is statistically significant at conventional levels starting with the 25%-50% threshold for VA productivity and, with one exception, from the 10%-25% threshold in the case of turnover productivity.

Enterprises that belong to a domestic or foreign group tend to be more productive, as indicated by the positive coefficient estimates. However, this association appears statistically weaker for VA-based productivity. Market competition intensity does not seems to bear a statistically significant relationship with turnover productivity, but displays a negative and significant association with value added productivity. This indicates that the perception of stronger competition on the main market is linked to lower productivity levels in terms of value added. Considering that the economic literature generally attributes a positive impact of competition on productivity, this result deserves further investigation.[28]

Overall, the results on the association between MPs importance and productivity appear qualitatively aligned with the economic literature reviewed in this work. At the same time, the relatively small sample size and the cross-sectional nature of the data suggest a cautious evaluation of the findings. Sensitivity of the results to changes in samples and econometric specification should also be noted. Additional data from subsequent CIS waves and methodological improvements in the research design are required to assess the robustness of these results. Methodologically, the inclusion of capital input to allow an assessment of total factor productivity should be regarded as a highly desirable development for the analysis

[23] Estimations are cross-sectional and performed by ordinary least squares. The estimates are weighted using CIS 2018 sampling weights. Standard errors are clustered by NACE Rev. 2 Division. The p-values are obtained by wild bootstrapping using the command *boottest* (Roodman et al., 2019) in STATA® 17. Results obtained using default STATA® 17 heteroscedasticity-robust and cluster-robust standard errors do not fundamentally change the conclusions.

[24] As the dependent variables are in logarithm, these percentages are calculated as $(e^{\hat{\beta}_1} - 1) \times 100$, where $\hat{\beta}_1$ is the estimated coefficient on the MPs index from Table 3.

[25] Due to missing values for the included variables, there are differences between samples for value added and turnover productivity as well as between each of these and the full sample used to calculate the standardised index. However, the mean and the standard deviation of the index in the first two samples are very similar, and very close to the zero mean and unit standard deviation implied by the standardisation in the full sample.

[26] When looking at results with and without financial firms, it is important to remember that the MPs ratings for each regression have been standardised with reference to different samples. Therefore, direct comparison across samples of the magnitude of the effects should take this into consideration.

[27] See Syverson (2011) for the role and limitations of human capital in explaining productivity differential.

[28] See, for instance, Holmes and Schmitz (2010) and Syverson (2011).

2.4.5

Conclusions

Focusing on the service-driven Luxembourgish economy, this work investigates the links between management practices (MPs) and enterprise performance at firm level. This relationship has received considerable attention in the economic literature. Notably, research based on the World Management Survey (WMS) methodology and related survey tools typically points to a positive association between MPs quality and performance.

Despite its relevance, firm-level evidence for Luxembourg on this relationship is lacking. This study partially fills such gap using data from the Community Innovation Survey (CIS) and Structural Business Statistics (SBS). In particular, the CIS 2018 wave for Luxembourg includes ad hoc questions on two MPs inspired by the literature on the topic. Following mainstream research, these data allow an assessment of the association between MPs importance and enterprise performance. Focusing on labour productivity as performance indicator, the research first proposes a set of descriptive statistics and then move to a more formalised regression model.

The descriptive analysis suggests that enterprises tend to consider the two MPs as jointly important for their business. Moreover, consistently with results from the reviewed literature, firms that attach higher importance to each MPs tend to be larger or more productive. In addition, firms that occupy a more educated labour force or that face stronger market competition tends to consider individual MPs as more important for their business. This is compatible with the view that such factors promote management quality, as generally maintained by the literature considered in this work. While informative, it is important to remember that these descriptive statistics offer a preliminary assessment of the main patterns that require confirmation through additional analysis.

The correlation between labour productivity and MPs importance is further evaluated in a regression framework. This allows considering the influence of additional factors on firm-level productivity differentials. The regression results tend to confirm a positive statistical association between MPs importance and labour productivity. When excluding financial firms, this association emerges regardless of whether productivity is measured in terms of sales turnover or value added. In case of turnover productivity, the association appears sizeable and significant regardless of the inclusion of financial firms. Overall, these findings suggest that firms that consider MPs as important for their business tend to have higher labour productivity. This holds after controlling for other factors affecting productivity, such as workforce education and group affiliation. It is important to observe, however, that the analysis does not imply a causal effect of MPs importance on productivity.

Therefore, despite potential limitations in the number of MPs and in the structure of the survey questions, this analysis delivers results that are qualitatively aligned with the economic literature referenced in this work. Nonetheless, the relatively small sample size and the cross-sectional nature of the data suggest a cautious evaluation of these findings. Additional data from subsequent CIS waves and methodological improvements in the research design are required to evaluate the results robustness. In terms of methodology, the inclusion of capital input to allow an assessment of total factor productivity is certainly worth mentioning as a highly desirable development. Even so, these results can be considered sufficiently encouraging to justify and support further research on this topic.

2.4.6
Appendix

Community Innovation Survey (CIS) 2018 target population according to NACE Rev. 2

The target population of the CIS 2018 includes the NACE Rev. 2 Sections B, C, D, E, H, J and K as well as Divisions G46, M71, M72 and M73.

B Mining and quarrying

C Manufacturing

D Electricity, gas, steam and air conditioning supply

E Water supply, sewerage, waste management, and remediation activities

G46 Wholesale trade, except of motor vehicles and motorcycles

H Transportation and storage

J Information and communication

K Financial and Insurance Activities

M71 Architectural and engineering activities; technical testing and analysis

M72 Scientific research and development

M73 Advertising and market research

For additional methodological information on the CIS 2018, see https://ec.europa.eu/eurostat/cache/metadata/en/inn_cis11_esms.htm. For the CIS 2018 for Luxembourg, see https://ec.europa.eu/eurostat/cache/metadata/EN/inn_cis11_simsci_lu.htm

Structural Business Statistics (SBS) dataset

The first component of the Structural Business Statistics (SBS) dataset is the annual Structural Business Survey conducted by STATEC. The survey covers enterprises above a certain threshold for employment or turnover as well as a random sample of smaller units. Survey data are then integrated with additional administrative sources. Estimation and imputation procedures are also applied to deal with the different coverage between survey data and administrative sources.[29] In comparison to the survey sample, this substantially increases the number of firms available for the analysis.

Acknowledgements

We wish to thank the US Bureau of Census for allowing general reference to the MOPS 2015 questionnaire for the management practices questions included in the CIS 2018 for Luxembourg. We are grateful to Xi Chen, Kelsey O'Connor, Cesare Riillo and particularly Maxime Pettinger for helpful discussions on various aspects of the work. We also thank Georges Zangerlé for invaluable help and insightful advice with CIS and SBS data. The Authors remain responsible for any error.

[29] For additional methodological information, please see:
https://statistiques.public.lu/en/donnees/methodologie/methodes/entreprises/structure-activite-entreprises/sse.html
https://ec.europa.eu/eurostat/cache/metadata/EN/sbs_h_esms_lu.htm

2.4.7
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2.5
R&D, innovation inputs and productivity: The role of National Innovation Systems

2.5.1
Introduction

Almost 90 years ago, Schumpeter (1934) argued that innovation plays a crucial role in economic and social changes. In particular, innovation activities are important for total factor productivity growth. Under the Schumpeterian perspective, Aghion and Howitt (1992) have proposed innovation-based endogenous growth models or innovation-led growth models that clearly show the role of innovation for long-term growth and productivity gains. Thus, research and development (R&D) policies and R&D expenses targets are high on the policy agenda. With the exception of the years during and immediately after the financial crisis of 2007, R&D expenses are growing fast in higher education, government as well as in the business sector (OECD, 2022). In the OECD countries, the level of R&D spending rose by 2.7% in real terms during the last decade. Since 1995, R&D intensity (R&D expenses over GDP) grew from 2% to 2.4%. Against this background, a key question is the ability of countries to turn these expenses into innovations.

There is an extensive body of work about the production of knowledge/innovation, e.g. Griliches (1990), Griliches (2007), Madsen (2008) or Verba (2022) among many others. In general, these studies link R&D expenses (either in level or as stocks of R&D) and the number of researchers to numbers of patents granted in countries, as a measure of innovation. To maximise innovation output from R&D, there is a need to influence both speed and direction of innovation (Hekkert et al., 2007). This requires a well-designed management framework, a National Innovation System. A National Innovation System is the network of institutions in the public and private sectors whose activities and interactions initiate, import, modify, and diffuse new technologies (Freeman, 1987).

This paper investigates whether or not the National Innovation System explains cross-country differences in the production of innovations.

Firstly, we evaluate the impact of the stock of accumulated R&D and the number of researchers on both patents granted and the publication of scientific documents in OECD countries, and additionally Argentina, Russia and Singapore. We use Data Envelopment Analysis (DEA), a popular non-parametric mathematical programming approach for performance assessment and benchmarking, first proposed by Charnes et al. (1978). The aim of this analysis is to gauge to what extent a country turns research and development inputs (R&D and researchers) into innovation outputs (patents and publications) compared to other countries. In a second step, we analyse the factors that explain the differences in country's efficiency in transforming R&D into patents and documents. In particular, we analyse how differences in National Innovation Systems affect the "production" of innovation.

As emphasized by the OECD (1995), National innovation systems act as facilitators for interactions among various actors involved, and in our analysis, we focus on key characteristics that have been acknowledged as important in the literature. These are public-private collaborations, Intellectual Property Protection rights, workforce training, and university expenses. According to Wirkierman et al. (2018), the collaboration between the private and public sectors holds particular significance in enhancing technological capabilities. We first focus on two important types of collaborations: inter-industry collaboration (in the form of cluster development), and industry/university collaboration. On one hand, inter-industry collaboration in the form of technological clusters stimulates knowledge spillovers, encourages cooperation and stimulate the identification of new technology trends and potential innovation (United Nations Economic Commission for Europe, 2013). On the other hand, industry/university partnerships play a crucial role in facilitating the assimilation and development of new technologies by firms (Veugelers, 2016).

We also investigate if intellectual property protection rights impact inefficiency. This is because it is pointed out that weak intellectual property protection rights might exacerbate free rider behaviour (Shapiro and Willig, 1990) and lower R&D activities. Another important aspect of National Innovation Systems is the absorptive capacity of firms (Kneller and Stevens, 2006). A skilled workforce will increase the ability of firms to implement new technologies (Abramovitz, 1986). Bauernschuster et al. (2008) indicate that continuous training of the workforce increases the innovative capacity of firms.

Another element we consider is the share of university gross expenses in R&D in total expenses. As explained by Svarc et al. (2020), this share might be seen as a proxy of the production of more fundamental research, which is the prerequisite for many applied research activities.

This paper is organised as follows: Section 2 presents the data used to compute inefficiency and sources of inefficiency. Section 3 summarizes results and estimates of the effect of National Innovation Systems on inefficiency. Section 4 compares Malmquist Total Factor Productivity index with and without innovation inputs, and the last Section concludes.

2.5.2
Data

This document uses a balanced panel dataset of 30 countries including European and OECD countries plus Argentina, Russia and Singapore from 2006 to 2019[1].

We consider four inputs and two R&D outputs. Two inputs are, respectively, the number of researchers in the business sector (mainly working in non-financial corporations) and in the non-business sector (working in university and/or public research departments). Rather than considering R&D expenditures, we compute two R&D capital stocks, respectively for the business and the non-business sector. This distinction aims to reflect countries specificities where R&D is mainly public, while in other countries R&D is mainly business oriented. It is also justified by the fact that public R&D typically focuses more on fundamental research (generating scientific publications), while business R&D is geared toward business innovations and patenting (Svarc et al., 2020).

The innovation outputs are: produced patents and academic publications. Data on patents are sourced from the World Intellectual Property Organization. Data on scientific publications come from Scimago, a portal that collects citable scientific documents drawn from over 34,100 titles from more than 5,000 international publishers.

R&D capital stock (KRD_t) are figures computed using the perpetual inventory method and the accumulation of total Gross Domestic Expenditure on R&D (GERD) in constant 2015 PPPs Prices in USD (I_t) published by the OECD Main Science & Technology Indicators (MSTI).

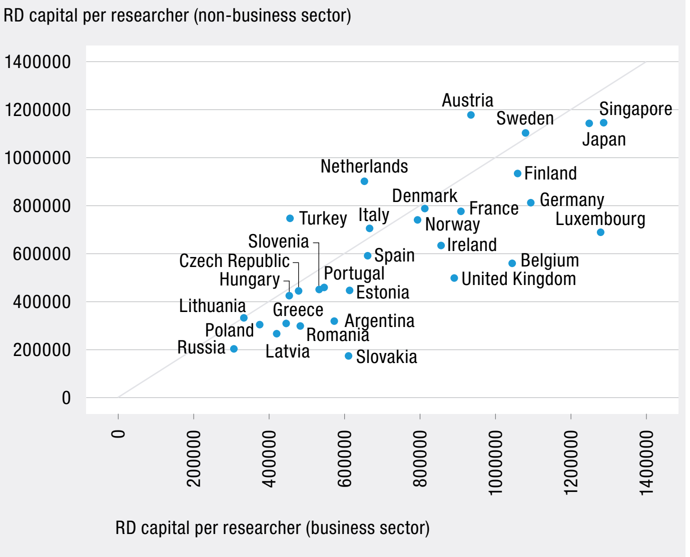
$$KRD_{t+1} = (1 - \delta)KRD_t + I_t$$

Following the work of Bernstein and Mamuneas (2006), Corrado et al. (2006) and Hall et al. (2010), we use a depreciation rate (δ) of 15 percent, the initial value is based on the average growth rate of GERD (g) for the business sector and the non-business sector. And, as in Hall et al. (2010), the capital stock is computed as,

$$KRD_t = \frac{I_t}{\delta + g}$$

Tables 2 and 3 in Appendix provide some descriptive statistics on R&D capital. Eastern European countries and Luxembourg have lower R&D capital and fewer researchers compared to other countries. Clearly there is a size effect, small countries (in terms of population) tend to have less researchers, while countries with lower GDP tend to spend less in R&D. When the amount of R&D capital per researcher is computed, a different picture emerges. Singapore and Luxembourg have the highest ratios of R&D capital per researcher, with 1.29 million USD and 1.28 million USD respectively. It is only 0.31 million USD in Russia or 0.91 for France. If Luxembourg has a very high ratio for the business sector, the country is close to the sample average regarding the non-business sector, with an average value of 0.68 million of USD. Figure 1 plots average values of R&D capital per researcher in the business and the non-business sector for countries.

Figure 1
R&D capital per researcher business versus non-business sector – averages 2006-2019 (USD)



Source: Author's computations based on WIPO and Scimago data

One may note that the ratios of capital to researchers in the business and the non-business sector are similar for most countries, as indicated by the proximity of the country points to the grey line (in Lithuania both ratios have a value of 0.33 million, in Denmark it is 0.81 and 0.78 million of USD). In general, researchers in the business sector have slightly more capital than in the non-business sector (R&D capital deepening). A notable exception is Luxembourg where the endowment in capital is significantly higher for the business sector.

To proxy innovation outputs, we consider two variables. The first one is patent that is often used in studies about the knowledge production function (e.g. Wang, 2007). As explained by Griliches (1990), patents are a good indicator of differences in inventive activity across different firms. Patents can be used as an indicator to signal innovative capabilities (Czarnitzki et al., 2014). However, not all innovation outputs can be patented. For example, scientific theories, mathematical methods, computer programs or procedures for surgical or therapeutic treatment, or diagnosis, to be practised on humans or animals, cannot be patented. Thus, all these innovations, in many cases, result from research activities that have been financed by R&D expenditures, but might generate only academic publications. Thus, citable documents published is our second proxy for innovation output. Few studies have used citable documents to proxy innovation output, with the exception of studies that focus on the productivity of universities (e.g. Courtioux et al., 2022).

[1] Countries included in the panel are: Argentina, Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Russia, Singapore, Slovakia, Slovenia, Spain, Sweden, Turkey and the United Kingdom.

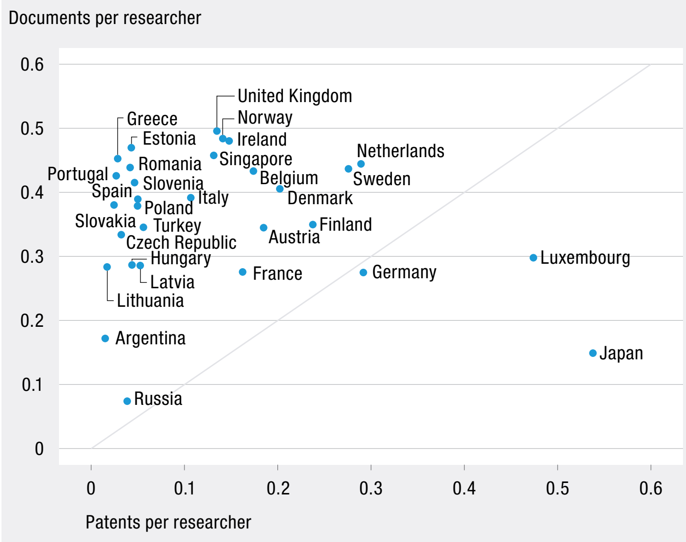
Looking at the number of patents and citable documents published, again, Eastern countries have the lowest figures (Lithuania, Estonia, Latvia, Slovakia, Slovenia). For patents, results are similar. However, when divided by the number of researchers we observe striking differences between countries. Figure 2 shows that countries like Japan or Luxembourg have more patents per researcher than other countries (respectively a ratio of 0.54 and 0.47) compared to 0.04 for Russia, 0.16 for France 0.29 for Germany. This does not come as a surprise, Japan's economic growth has been often attributed to its superior research and development capabilities, but the situation is deteriorating since the 2010s (Nishimura et al., 2022). In general, countries publish more documents than patents. Luxembourg performs well in terms of patent applications, but OECD (2008) notes that it might be in part a statistical effect owing to the number of firms head-quartered there.

Following Han (2007), we use patent data and citable document to compute two knowledge stocks. The inter-temporal identity used to derive stocks of patents and scientific documents is identical to the one used in deriving capital stocks, with the substitution of R&D by either patents or documents. We will use these stocks as innovation inputs to produce goods and services (GDP) and compute TFP indicators for countries.

However, R&D expenditures and the number of researchers are not sufficient to describe the complex process of innovation. The set of distinct institutions which jointly and individually contribute to the development and diffusion of new technologies and which provides the framework within which governments form and implement policies to influence the innovation process (Metcalfe, 1995) also matters. The National Innovation System plays an important role in fostering innovation activities. The OECD (1995) quotes two important features of National Innovation System: Industry alliances and Industry/University interactions. The World Economic Forum provides an assessment made by businessmen to evaluate these elements: State of cluster development and University/Industry collaboration in R&D. These two indicators are based on surveys collecting the views of representative businessmen on these two topics by providing a grade between 1 and 7 (7 indicates the best value) (Schwab, 2019)[2].

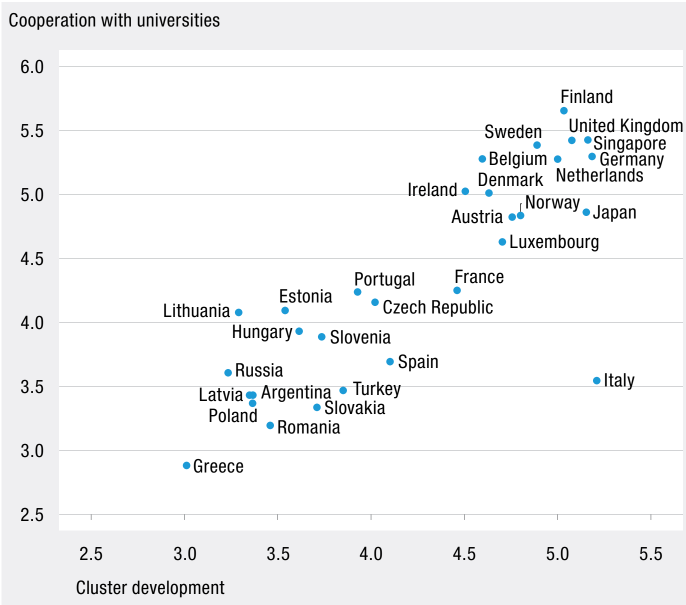
Figure 3 shows that cluster development[3] and industry/university collaboration are highly positively correlated. Countries with higher levels of industry/university collaborations tend to have a greater presence of clusters. Moreover, the panel can be divided in two groups of countries. A first group of mainly Eastern European countries (Latvia, Poland, Romania, Russia, Slovakia, Lithuania, Estonia, Slovenia and Hungary), and Southern European countries, such as Spain and Portugal. These tend to have low cluster development and low collaboration with universities. Portugal, for example, has a lower cluster development than other countries as the regional economic development policies have disregarded the importance of fostering the creation of clusters (Salvador and Chorincas, 2006).

Figure 2
Citable documents versus patents per researcher – averages 2006-2019



Source: Author's computations based on WIPO and Scimago data

Figure 3
University/Industry cooperation versus industry alliances – averages 2006-2019



Source: Author's computations based on World Economic Forum data

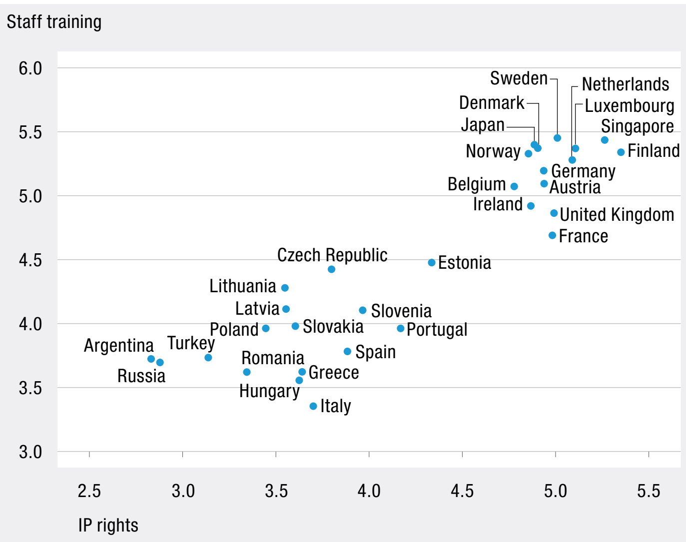
[2] These two variables are contextual variables and not inputs as individual businessman cannot change the national value (the perception of others) as well as the central planner (Government). This is in line with the main hypothesis of model of endogenous growth such as Romer (1986), where, for example, managers can change the stock of knowledge in their firm but cannot change the total stock in the economy that is generating positive externalities. Here, for example, a firm might decide to engage in collaboration with universities but cannot influence other managers on this aspect.

[3] Clusters are a network of firms which tend to be located in relatively close geographical proximity and whose cross-sectoral linkages generate and renew local competitive advantage (Raines, 2017).

At the opposite, we have a group of Nordic countries (Finland, Sweden, Norway, Denmark) and Western European countries (Belgium, United Kingdom, Germany, Ireland, Luxembourg) characterized by high cluster development and university/industry collaboration. For the case of Nordic countries, these high scores translate the successful implementation of a triple helix innovation model in which universities, government authorities, and industrial firms cooperate in order to produce innovation (Solesvik, 2017; Arnkil et al., 2010). An outlier is Italy with high cluster development but low collaboration university/industry. Interestingly, Abramo and D'Angelo (2009) found that most research projects' results of leading public research scientists and Italian universities do seem to have immediate industrial applicability, but in one third of the cases there are no Italian companies able to exploit the results. Italy registers a low propensity to capitalize on the results of public research (Abramo et al., 2009).

As explained in OECD (1995), a key NIS policy that enhances innovative capacity is staff training. Human capital determines firms' capacity to absorb new technologies (Abramovitz, 1986). Brunello et al. (2007) clearly show that R&D investment and training exhibit a complementary relationship. Bauernschuster et al. (2008) provide (weak) evidence that continuous training improves firm's innovations. For the case of Norway, where staff training is extensive (5.3), Boring (2017) provides evidence that training stimulates new ideas, creativity and increases innovation in firms. From Figure 4, one can see that Italy has the lowest score for staff training (3.4). This observation might provide an explanation for the limited ability of companies to capitalize on research outcomes, as highlighted by Abramo and D'Angelo (2009).

Figure 4
Staff training versus strength of IP rights – averages 2006-2019



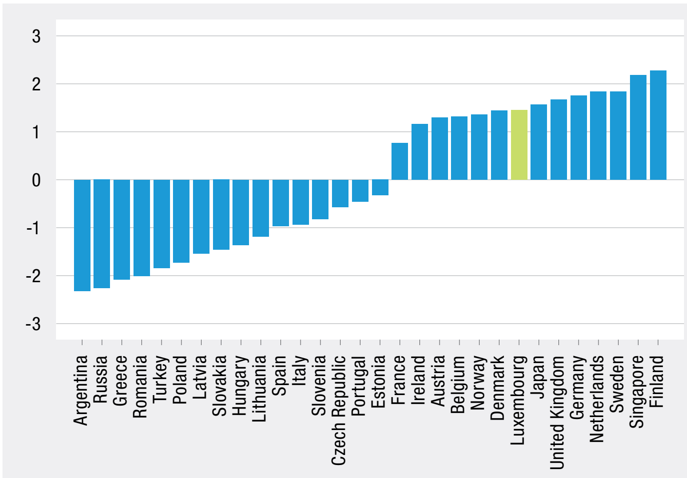
Source: Author's computations based on World Economic Forum data

The last element that characterizes country's innovation systems is the strength of intellectual property protection rights. Intellectual property (IP) protection rights help innovators to temporarily gain monopoly power from successful innovation activities (Greenhalgh and Rogers, 2007). While imperfect appropriability increases the incentives of firms to free-ride on each other's R&D investment (Shapiro and Willig, 1990). Arguably, low assessment of the strength of IP rights might also signal lack of awareness about IP rights as well as low innovative capacities of firms. For example, this is the case of Poland (Clayton et al., 2023). Poland exhibits a property-protection rights score of 3.8 compared to 6.2 for Singapore. The lowest value for IP rights is for Argentina (2.9). Castrillo (2017) indicates that Argentina has a long and poor image as a country that disregards IP rights. Russia is also a country with a low evaluation of IP rights (2.9). Aleksashenko (2012) attributes it to excess bureaucracy, corruption and absence of independent judicial protection property rights.

To mitigate multicollinearity (due to the high correlation among contextual variables, as shown in Table 4 in Appendix) and maintain a manageable number of parameters to be estimated, we substitute contextual variables with a composite indicator variable obtained through principal component analysis (see Joliffe and Cadima (2016) for a presentation of the method).

The weights to aggregate the variables are computed on average values of each contextual variable and these weights are used to compute yearly aggregates. In other words, the weights are constant across year. The first component explains 90 percent of total variance and is highly positively correlated with the four variables (Cluster Development, 0.89, Industry/University cooperation, 0.96, Staff development, 0.94, IP rights, 0.98).

Figure 5
National Innovation System composite index – averages 2006-2019

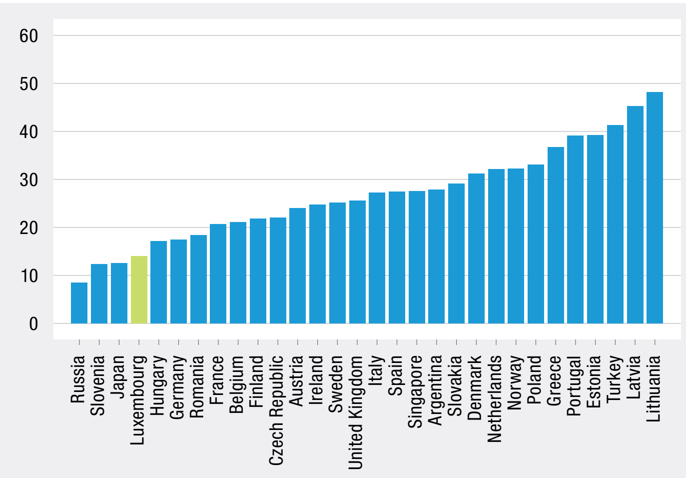


Source: Author's computations based on World Economic Forum data

One may argue that these variables are subjective and might not reflect the objective reality of National Innovation Systems. We quote Okun (1960) about the use of confidence surveys, that are also subjective assessments, to describe and predict the economic evolution of countries: "the population can sense the presence of a viruses in the atmosphere and still be totally unable to predict who will be stricken". Interestingly, the ranking implied by our composite index echoes the taxonomy of National Innovation Systems proposed by Wirkierman et al. (2018) based on the Community Innovation Survey firm level data. Wirkierman et al. (2018) classifies Austria, Belgium and Norway as "Top-notch NIS" countries. Our composite indicator also ranks these same countries highly in terms of all collaborations (see Figure 3). Netherlands and Sweden rank high (labelled as the linear R&D-based NIS). (These countries rank above average for all indicators used to compute our composite index.) On the bottom of the ranking, we have countries that are labelled Coping-NIS, Spoiled under-performing NIS and embryonic NIS following the taxonomy of Wirkierman et al. (2018). Finland ranks first for our indicator as, for most indicators, this country exhibits among the highest values. The high score of Finland on our indicator is not surprising, considering that innovation policy is regarded as one of the most vital public policies in the country. But also successful university reforms to improve research careers, research infrastructures and sectoral research. On the contrary, countries like Greece rank low, primarily due to their limited absorptive capacity of firms, as previously highlighted in OECD (2008).

Last, as explained by Veugelers (2016), universities play three important roles: their teaching, universities disseminate knowledge and improve the quality of human capital employed in society; through the research they perform, universities extend the horizons of knowledge; and by their third-mission activities, they transfer their knowledge to society. García-Vega and Óscar Vicente-Chirivella (2020) provide evidence that technology transfers from universities foster firm innovativeness.

Figure 6
Share of R&D university expenses in total R&D expenses – averages 2006-2019



Source: Author's computations based on OECD MSTI data

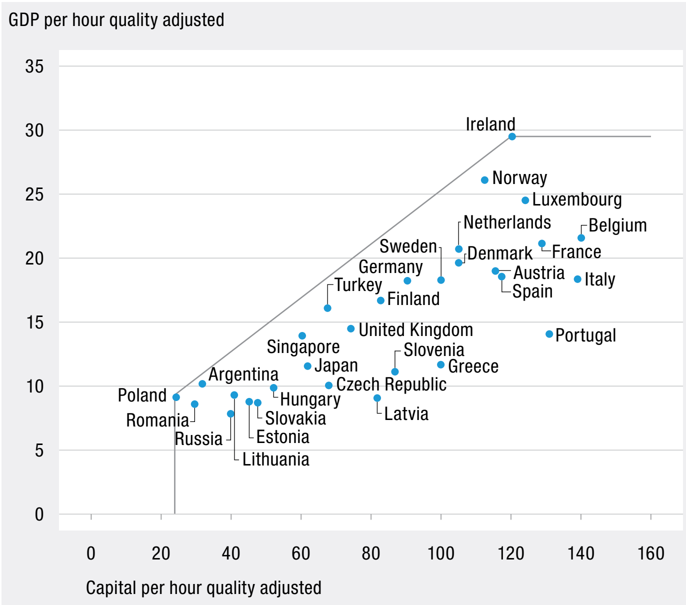
Thus, we look at the share of universities' R&D expenses in total expenses. This variable is not included in the computation of the composite indicator since the indicator is composed of variables that capture perceptions rather than expenses.

In the first step, we will use data on R&D capital and the number of researchers to assess the efficiency of countries in converting inputs into innovation outputs, such as patents and citable documents. In the second step, we will seek to explain the variations in efficiency of this conversion process by considering contextual NIS variables.

This paper focuses on the production of innovation, many studies highlight the importance of innovation for economic growth (Ibrahim, 2023). Thus, in a last step, we compute Malmquist total factor productivity (TFP) index using as inputs: physical capital and qualified labour plus innovation inputs (knowledge stocks based on patents and citable documents) and as outputs goods and services produced (Gross Domestic Product, GDP)[4]. To contrast our results, we will compute Malmquist total factor productivity indicators without innovation inputs.

Figure 7 indicates that, on average, countries with higher capital deepening (capital stocks divided by hours quality adjusted) have higher GDP per hour quality adjusted. Countries are more or less efficient in turning inputs into outputs, for example Portugal and France have relatively similar capital deepening (respectively 131 and 129 thousand of USD) but very different GDP per hour (respectively 14 and 21 thousand of USD).

Figure 7
GDP versus capital per hours quality adjusted – averages 2006-2019



Source: Author's computations based on Penn World Data

[4] In this study, economic inputs and GDP are sourced from the Penn World Tables (Feenstra and Timmer (2015) present the data). Physical capital corresponds to equipment and is measured in USD in constant 2015 prices while labour is hours adjusted for quality. As explained in Feenstra and Timmer (2015), hours worked are adjusted by an index of human capital that takes into account the average years of schooling, linearly interpolated from Barro and Lee (2013), and an assumed rate of return for primary, secondary, and tertiary education, as in Caselli (2005).

2.5.3
National Innovation Systems and efficiency

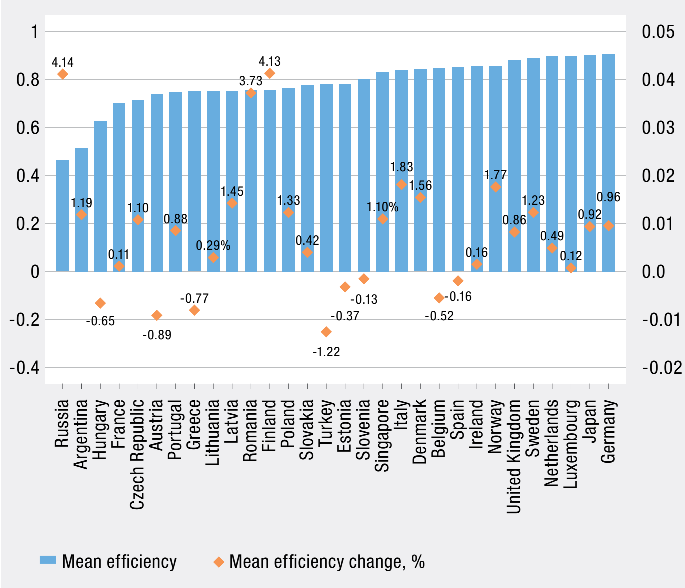
This section presents the result on innovation efficiency and the role of National Innovation systems in explaining inefficiency differences (inefficiency is one minus efficiency) differences across countries. We now present the country's efficiency scores in transforming research inputs, namely R&D capital and the number of researchers, into innovation outputs. In Figure 8, the blue bars depict the efficiency levels for the 30 countries under investigation. These scores range empirically from 0.5 to 0.9, with higher scores indicating higher efficiency.

Our results indicate that the least efficient country in producing innovation outputs is Russia (Figure 8). Several authors have noted the low performance of the Russian National Innovation System (Gianella and Tompson (2008) speak of a Russian innovation paradox). Many explanations have been proposed for this result: insufficient evaluation of public R&D spending (Graham and Dezhina, 2008), degradation of human capital (Gaddy and Ickes, 2013), lack of alignment of regional innovation efforts as explained by Crescenzi and Jaax (2017).

The second worst performance is Argentina. Bank et al. (2021) explain the Argentinian poor performance by low absorptive capacities (Figure 4 shows that staff training is far below sample average with a score of 3.7 compared to an average of 4.5) and weak cooperation between firms and universities (Figure 3 confirms this explanation, the sample average is 4.3 and the score for this country is 3.4).

Germany is on average more efficient than France. Robin and Schubert (2013) in their study suggest that differences in science policy, in particular less coordination and integration than what characterises French policies, reduce cooperation, thus generating less innovation output. In Figure 3 one can see that both indicators have a lower score for France compared to Germany, for collaboration with universities 4.2 for France and 5.3 for Germany and for cluster development, it is 4.5 to be compared to 5.2.

Figure 8
Efficiency (left axis) and efficiency change (right axis) for innovation activities – averages 2006-2019



Source: Author's computations

We now explain the differences in inefficiency scores (one minus efficiency scores computed) with the quality of NIS, as represented by our composite indicator, and with the share of university R&D expenses. We regress, using the bootstrap algorithm of Simar and Wilson (2007), inefficiencies on the National Innovation System indicator and the percentage of university R&D expenses in total expenses. A negative value indicates improvement in efficiency, a reduction of inefficiency. Marginal effects indicate that both variables reduce inefficiencies. However, the impact of an improved National Innovation System has a stronger effect in reducing inefficiency than university expenditures. On average, the impact of National Innovation System is to reduce inefficiency by 14 percent (the year 2014 is excluded as non-significant), while the percentage of university R&D expenditure decreases inefficiency by about 2 percent.

Table 1
Marginal effects on inefficiency

Variable	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Innovation System	-0.09	-0.09	-0.14	-0.07	-0.04	-0.22	-0.24	-0.26	-0.46	-0.26	-0.20	-0.14	-0.09	-0.09
p. val.	0.00	0.00	0.00	0.17	0.26	0.04	0.02	0.03	0.28	0.07	0.02	0.00	0.00	0.00
University R&D	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.04	-0.02	-0.01	-0.01	-0.01	-0.01
p. val.	0.00	0.00	0.00	0.00	0.00	0.11	0.03	0.03	0.23	0.04	0.08	0.00	0.00	0.00

Source: Author's computations

2.5.4
Malmquist TFP and innovation inputs

So far, we have focused on the production of innovation as there is a general consensus that innovation is an important driver of economic growth, as exemplified in the model of Aghion and Howitt (1992). The last step in our analysis is computing Malmquist TFP indices using GDP as an output and two different sets of inputs. The first set only includes labour (hours adjusted for quality) and physical capital, TFP_{ref}, while the second set includes labour, physical capital, and knowledge stocks based on patents and citable documents (innovation inputs) TFP_{ino}. We then compute sources of changes in Malmquist between the alternative specifications with different inputs set. As explained in Sickles and Zelenyuk (2019), TFP change can be decomposed as the product of efficiency change (EFF) and technical change (TECH).

$$TFP = EFF \times TECH$$

Taking logs, one has an estimate of the growth rate of TFP change that decomposes into the sum of log efficiency change and log technical change (contributions to TFP growth) and we take the difference between the two decompositions. Basically,

$$\log(TFP_{ino})-\log(TFP_{ref}) = [\log(EFF_{ino})-\log(EFF_{ref})] + [\log(TECH_{ino})-\log(TECH_{ref})] \quad (1)$$

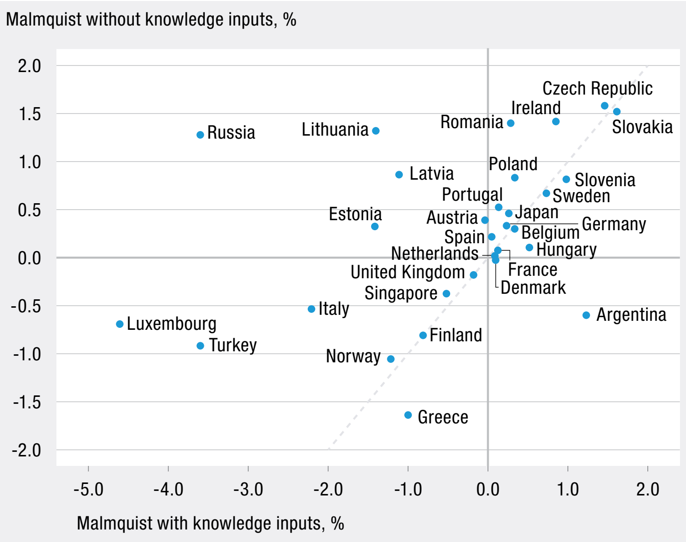
Figure 9 presents a comparison of TFP indices obtained with the standard set of inputs with the TFP indices obtained with the augmented input set, which includes knowledge/innovation inputs. This depiction allows us to visually compare results and as such to “gauge” the relevance of the knowledge inputs set for those economies. For some countries, using different input sets marginally change the value of TFP, for example, Finland, Denmark, Spain, Belgium, Japan or Sweden.

For only three countries, TFP using innovation inputs have a significantly increased productivity growth (Argentina, Greece, and Hungary). For a small set of countries, TFP growth dramatically decreased: Luxembourg and Russia are two extreme examples (see Figure 9). For Luxembourg we believe that large losses in technical changes indicate a possible statistical artefact. That is, many patents allocated to Luxembourg might not be the results of activities carried out in Luxembourg. Instead, they might be registered by a multinational whose headquarters is located in Luxembourg. As a result, they might not have any real economic impact on the local economy. In this case, there is an overestimation of innovation inputs given the level of GDP. We note, in particular, that during the financial crisis the growth rate of TFP is -7 percent and -5 percent in 2007 and 2008, and, when adding knowledge inputs, the decrease is -19 and -17 percent!

For the case of Russia, we propose a slightly different explanation but still linked with the idea of an overestimation of inputs. Several studies, e.g. Ito (2012), indicate that the evolution of the Russian GDP is highly correlated with TFP evolution, and is correlated with the price of oil. Thus, knowledge inputs are likely to play a minor role to increase GDP.

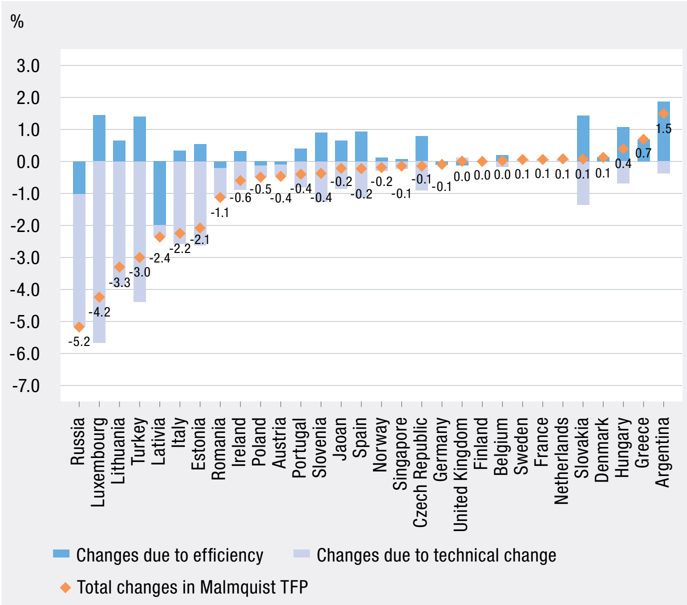
The decomposition presented in equation (1) allows us to track changes due to the introduction of innovation inputs in the computation of Malmquist TFP. It is interesting to note that changes are mainly due to losses in technical changes (Figure 10). For example, technical change is of about 4 percentage points lower in Russia when innovation inputs are considered. TFP is the non-explained growth of output that is not due to an increased use of inputs. In our comparison we add more inputs, innovation inputs that can be seen as reflecting technical progress. As a consequence, we reduce the unobservable part that is otherwise attributable to technical progress.

Figure 9
Malmquist TFP indicators – averages 2006-2019



Note: The dotted line indicates equality between the two Malmquist TFP indexes.
Source: Author’s computations

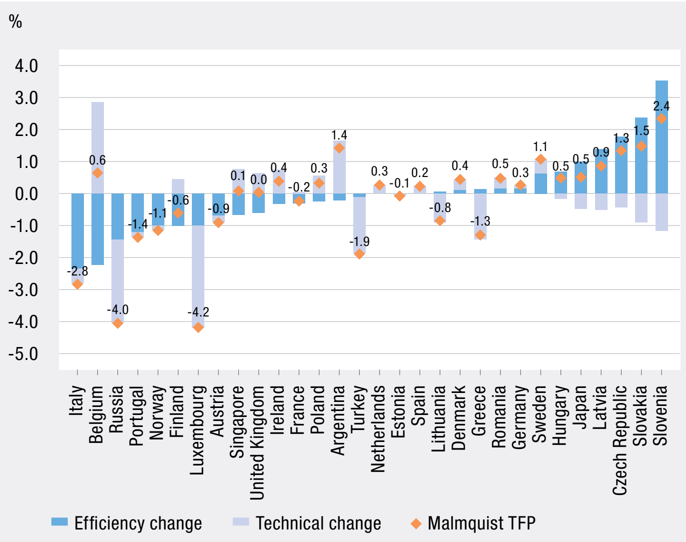
Figure 10
Sources of Malmquist TFP changes – averages 2006-2019



Source: Author’s computations

Last, we present the average value of Malmquist TFP when considering innovation inputs and its decomposition into efficiency change and technical change. Some countries exhibit technical regress (Figure 11). This means that, for a given level of inputs, countries are not able to produce the optimal level of GDP that was observed in the past. Technical regress has been observed in many studies, e.g. Deliktas and Balcilar (2005) or Chen and Yu (2014), and in most cases they provide no explanations why. We propose several possible explanations: as mentioned for the case of Luxembourg it might be the case that inputs are overestimated in particular patents, we do not consider labour hoarding as well as capacity utilisation rate. We leave this issue for further investigations.

Figure 11
TFP and TFP decomposition with innovation inputs – averages 2006-2019



Source: Author's computations

2.5.5 Conclusions

This document provides evidence that National Innovation Systems matter to the efficient production of innovation in countries. As a consequence, a country might improve its efficiency to produce innovation by easing inter-firms cooperation, as well as enhancing collaboration between universities and firms or improving the credibility and effectiveness of intellectual property rights. Another efficiency leverage is staff training that increases the absorptive capacity of firms. We also show that fundamental research is an important aspect of innovation as it is the basement of much applied research.

However, this work suffers from several drawbacks. As stated by OECD (2008), at least for the case of Luxembourg, the number of patents might be a statistical artefact due to the large number of headquarters of multinational firms located in the country. Another data issue, while it might not be the most frequent case, some patents and citable documents might result from people who are not researchers but are workers-employees and not funded by R&D expenses. In this case we fail to measure accurately the set of inputs. For example, Walsh and Nagaoka (2009) show that about 40 percent of patents granted to US small firms result from the activity of people who do not have an R&D functional affiliation in the firm, they are not researchers. Moreover, a firm might choose secrecy rather than patenting and/or the publication of scientific documents, therefore some innovations are not captured by our innovation outputs (Fedorenko et al. (2023) provide a nice survey on secrecy).

A possible methodological extension could be to consider the production of innovation and goods and services (GDP) in the framework of a cooperating network. In a first stage is the production of innovation outputs that are used in a second stage as inputs to produce goods and services. But the two sectors coordinate in order to maximise the positive outcome for the economy: innovation outputs and the creation of goods and services (see Li et al. (2012) for a presentation of network DEA). We conclude with a final remark. As in almost all studies about innovation, we implicitly assume that patents and scientific publications correlate with the technological sophistication of production process in economies. If a country is producing less innovation outputs, it is still possible to incorporate the newest technologies through investment in tangible or intangible capital goods/assets. But we still believe that countries that innovate the most are more able than others to use more efficiently inputs to produce outputs.

2.5.6
Appendix

Table 2
Variable averages 2006-2019

Country	KRD business	KRD non-business	Researcher business	Researcher non-business	Patents	Documents	Capital K	Qualified hours	GDP
Argentina	5901.20	265720.08	10290.50	60119.07	977.42	12139.28	2987306.91	93834.16	957471.76
Austria	42929.94	332511.81	45932.20	20211.79	12198.28	22793.92	2668975.23	23044.61	434944.30
Belgium	42626.14	230102.12	40833.95	29452.45	12212.78	30460.21	3169319.76	22609.87	487212.90
Czech Republic	15567.91	174118.52	32505.99	28179.13	1931.07	20288.14	2302551.30	33894.58	342047.41
Denmark	29161.23	233253.44	35940.18	21179.66	11522.78	23183.71	1485411.75	14124.63	277032.19
Estonia	1203.83	22883.85	1960.30	3668.00	241.07	2645.85	190070.16	4193.26	37131.07
Finland	32319.74	296376.20	30500.97	22723.24	12616.92	18640.78	1156442.79	13970.53	232756.36
France	222147.43	1824665.91	244461.29	168589.23	66840.57	114013.50	16694949.35	129509.18	2738076.51
Germany	411818.38	2523210.42	376742.50	222533.36	174593.57	165001.57	19580037.71	215971.84	3933015.67
Greece	4570.10	133269.06	10257.60	31262.83	1138.64	18805.35	2674053.83	26743.19	312687.74
Hungary	8791.55	100728.41	19396.07	17062.50	1578.64	10475.64	1279869.46	24408.87	241184.44
Ireland	13237.62	101628.86	15477.50	11477.76	3971.00	12946.21	1329291.02	11049.10	325729.56
Italy	91543.50	1181225.99	137581.82	120023.17	27527.07	100913.57	18478932.57	132812.95	2440462.60
Japan	755851.00	4442097.82	606078.57	278334.92	475891.57	132083.28	25823922.14	417607.84	4830374.92
Latvia	471.96	16949.09	1124.50	4600.42	297.21	1636.78	443520.64	5427.04	49389.15
Lithuania	876.11	41861.43	2627.42	9025.27	187.28	3313.64	336907.95	8201.05	76384.26
Luxembourg	4158.17	17420.99	3252.17	1814.43	2400.14	1516.57	240501.59	1939.32	47609.55
Netherlands	52281.87	553980.63	80183.04	43846.42	35813.64	55139.14	4427440.41	42105.93	873802.57
Norway	15877.63	201289.83	20022.65	19544.35	5542.64	19154.14	1484992.11	13211.05	344988.75
Poland	14228.17	277440.84	37886.27	65261.34	5113.64	39141.71	2558497.77	105078.49	958873.57
Portugal	9366.43	197059.43	17150.32	30864.74	1270.28	20430.85	2848049.55	21744.46	306001.43
Romania	5355.11	80667.06	11100.64	19456.85	1257.85	13416.78	1490426.02	50224.42	433463.58
Russia	132798.69	1122022.36	433402.78	397625.57	31191.28	61622.35	18793813.28	471028.00	3716915.78
Singapore	26983.86	303658.37	20987.55	18963.08	5219.50	18303.85	1666800.43	27610.43	385777.95
Slovakia	2514.35	32426.32	4112.32	13530.32	421.35	6698.85	701942.66	14756.16	128944.10
Slovenia	4556.50	33265.33	8519.57	5298.57	633.00	5738.57	481082.45	5542.10	61675.44
Spain	60882.76	980044.91	92225.73	118888.48	10402.42	82262.85	10955028.28	93487.06	1738360.54
Sweden	63478.73	369726.07	58835.35	24011.92	22819.00	36184.42	2568480.57	25649.30	468914.66
Turkey	26247.75	543529.73	57371.28	52233.88	6033.28	37857.21	7172627.35	106121.36	1705807.57
United Kingdom	166339.46	1384532.69	186686.67	200368.95	51904.57	191564.00	14054866.85	189016.66	2737716.85

Note: Variable in million USD exception made of hours in thousands, documents and publications are counts.
Source: Author's computations

Table 3
Variable averages 2006-2019

Country	University collaboration	Cluster	Staff training	IP rights
Argentina	3.430574494	3.36633581	3.727458234	2.935126416
Austria	4.820844277	4.757798441	5.095469491	5.751528957
Belgium	5.280290015	4.595760291	5.073180176	5.535703475
Czech Republic	4.155096707	4.022513539	4.424857634	4.229904806
Denmark	5.011370158	4.632838285	5.37106268	5.707708939
Estonia	4.094651887	3.53731321	4.477174264	4.946167888
Finland	5.64963417	5.035234774	5.337644322	6.299398637
France	4.24852789	4.460711598	4.694936243	5.809781545
Germany	5.296398469	5.185913367	5.196981479	5.749549029
Greece	2.883074697	3.013333301	3.621279813	4.021495538
Hungary	3.929542264	3.612826309	3.562676714	3.9975066
Ireland	5.019250711	4.50302009	4.919836081	5.660186473
Italy	3.54386931	5.209231153	3.359580862	4.098088034
Japan	4.86050463	5.154116082	5.395293655	5.682229036
Latvia	3.430089824	3.345606888	4.11271805	3.909898218
Lithuania	4.080650384	3.289538737	4.282673482	3.900148137
Luxembourg	4.629821925	4.703902487	5.373840037	5.979305957
Netherlands	5.274641038	4.999817997	5.275077368	5.953729959
Norway	4.837863342	4.801764375	5.329510283	5.639493452
Poland	3.372662587	3.364518451	3.961174227	3.760758088
Portugal	4.234796457	3.928184039	3.965090209	4.725888516
Romania	3.196018415	3.457370975	3.617179861	3.628427984
Russia	3.604921143	3.23098662	3.698479042	2.994620323
Singapore	5.421204565	5.161804863	5.436628507	6.185388238
Slovakia	3.339260877	3.707068416	3.986017065	3.972770228
Slovenia	3.88851726	3.734212672	4.107921758	4.451726496
Spain	3.693999935	4.10354853	3.783427496	4.343399606
Sweden	5.386423187	4.890519281	5.450892172	5.845216662
Turkey	3.46970182	3.850886271	3.735151682	3.346893023
United Kingdom	5.41832159	5.076938154	4.865645893	5.824236861

Note: Scores are between 1 (worst) and 7 (best).
Source: Author's computations

Table 4
Variable correlations 2006-2019

Variable	University collaboration	Cluster	Staff training	IP rights
University collaboration	1	0.824	0.905	0.897
Cluster		1	0.747	0.832
Staff training			1	0.909
IP rights				1

Source: Author's computations

Efficiency measurement and regression procedure

DEA (Data Envelopment Analysis) and SFA (Stochastic Frontier Analysis) are the main methods commonly used to estimate efficiency of a Decision-Making Unit DMU (countries, industries, firms…). Each method allows to handle the case of multiple inputs and multiple outputs. For example, Löthgren (1997) or Kumbhakar and Lai (2021) propose a stochastic frontier model that allows for multiple outputs. However, in practice, DEA is easier to use in the case of multiple outputs as it is the case in our study.

Let $X = (x_1, \dots, x_N) \in R^N_+$ be the set of inputs. For the production of innovation outputs, we consider four inputs: R&D capital and researchers in the business sector and the non-business sector. For the production of goods and services we also consider four inputs: qualified hours of work, physical capital, patents, and citable documents. The two last inputs are outputs in the first set of efficiency estimates. Let $Y = (y_1, \dots, y_M) \in R^M_+$ be the set of outputs. In the first model there are two outputs: patents and citable documents, in the second model there is only one output: GDP. The production is characterised by the production set $T = \{(Y,X) \mid X \text{ can produce } Y\}$. At this stage one should make an assumption on returns to scale: constant, variable or increasing. In this document we assume variable returns to scale for the production of innovation outputs and constant returns to scale for GDP[5]. Assuming constant returns to scale for GDP generation allows us to compute Malmquist total factor productivity (TFP) indexes that correctly assess TFP changes (see Bjurek (1996)). The second assumption to be made is to use an input or an output-oriented DEA model. In an input orientation, DEA minimizes input for a given level of output; in other words, it indicates how much a country can decrease its input for a given level of output. In an output orientation, DEA maximizes output for a given level of input; in other words, it indicates how much a country can increase its output for a given level of input. In the case of constant returns to scale, efficiency scores of countries are mathematically similar. However, policy implications are different. For this study we opt for an output orientation. We assume that countries are not willing to reduce R&D or to produce less citable documents and patents. The model to gauge efficiency is the following linear program,

$$\begin{aligned}
\text{Max} \quad & \vec{D}(x_{io}, y_{ro}) = \beta \\
\text{s.t.} \quad & \sum_{c=1}^{C} \mu_c x_{ic} \le x_{io}, \quad && i = 1, \dots, N \\
& \sum_{c=1}^{C} \mu_c y_{rc} \ge \beta y_{ro}, \quad && r = 1, \dots, M \\
& \mu_c \ge 0, && c = 1, \dots, C
\end{aligned}$$

[5] Bogetoft and Otto (2011) present a statistical test to select returns to scale, in our case the assumption of variable and constant returns to scale cannot be rejected.

If a country is able to provide the maximum output technically feasible given its use of inputs, the country will be said efficient and will receive an efficiency score of 1. Any deviation from 1 will indicate inefficiency. Sickles and Zelenyuk (2019) provide a nice introduction to DEA models.

A key question in this document is: does the National Innovation Systems explain why some countries are more efficient in producing citable documents and patents? A naive approach would have been to regress efficiency scores on a set of $Z = (z_1,\dots,z_K)$ contextual variables. Simar and Wilson (2007) explain that treating efficiency scores computed using model (1) as independent observations will lead to invalid inference on estimated parameters in the model. Thus, they suggest a double bootstrap procedure. The regression model is:

$$\beta_c = z_c\alpha + \epsilon_c$$

where α is a vector of parameters to be estimated. The error term ϵ is truncated normally distributed with zero mean, constant variance σ and left truncation at $1 - z_c\alpha$. The bootstrap algorithm is the following:

1. Compute efficiency scores $\hat{\beta}_c$ for all countries $c = 1,\dots,C$ using DEA.

2. Use those C^* ($C^* < C$) countries, for which $\beta_c > 1$ holds (inefficient countries), in a truncated regression (left-truncation at 1) of $\beta_c > 1$ on z_c to obtain coefficient estimates $\hat{\alpha}$ and an estimate for variance parameter $\hat{\sigma}$ by maximum likelihood.

3. Loop over the following steps 3.1-3.4 B times, in order to obtain a set of B bootstrap estimates $\hat{\beta}_c^b$ for each country c = 1, ..., C, with b = 1, ..., B.

   3.1 For each country c = 1,...,C, draw an artificial error $\tilde{\epsilon}_c$ from the truncated $N(0,\hat{\sigma})$ distribution with left-truncation at $1 - z_c\alpha$.

   3.2 Calculate artificial efficiency scores $\tilde{\beta}_c$ as $z_c\hat{\alpha} + \tilde{\epsilon}_c$ for each country c = 1,...,C.

   3.3 Generate c = 1,...,C artificial countries with input quantities $\tilde{x}_c = x_c$ and output quantities $\tilde{y}_c = (\hat{\beta}_c/\tilde{\beta}_c)\, y_c$.

   3.4 Use the N artificial countries, generated in step 3.3, as reference set in a DEA that yields $\hat{\beta}_c^b$ for each original country c = 1,...,C.

4. For each country c = 1,...,C, calculate a bias corrected efficiency score $\hat{\beta}_c^{bc}$ as $\hat{\beta}_c - (\frac{1}{B}\sum_{b=1}^{B} = \hat{\beta}_c^{bc} - \hat{\beta}_c)$.

5. Run a truncated regression (left-truncation at 1) of $\hat{\beta}_c^{bc}$ on z_c to obtain coefficient estimates $\hat{\hat{\alpha}}$ and an estimate for variance parameter $\hat{\hat{\sigma}}$ by maximum likelihood.

6. Loop over the following steps 6.1 – 6.3 B^* times, in order to obtain a set of B^* bootstrap estimates $(\hat{\hat{\alpha}}^b, \hat{\hat{\sigma}}^b)$, with b = 1,..,$B^*$.

   6.1 For each country c = 1,…,C, draw an artificial error $\tilde{\tilde{\epsilon}}_c$ from the truncated $N(0, \hat{\hat{\sigma}})$ distribution with left-truncation at $1 - z_c\hat{\hat{\beta}}$.

   6.2 Calculate artificial efficiency scores $\tilde{\tilde{\beta}}_c$ as $z_c\hat{\hat{\alpha}} + \tilde{\tilde{\epsilon}}_c$ for each country c = 1,…,C.

   6.3 Run a truncated regression (left-truncation at 1) of $\tilde{\tilde{\beta}}_c$ on z_c to obtain bootstrap estimates $\hat{\hat{\beta}}^b$ and $\hat{\hat{\sigma}}^b$ by maximum likelihood.

7. Calculate confidence intervals and standard errors for $\hat{\hat{\beta}}$ *and* $\hat{\hat{\sigma}}$ from the bootstrap distribution of $\hat{\hat{\beta}}^b$ and $\hat{\hat{\sigma}}^b$.

This bootstrap algorithm ensures that coefficients and their p-values are reliable. Note that we have panel data, and the procedure is designed for cross-section, then we compute regression coefficients for each separate year.

2.5.7
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Partie 3

Le Conseil national de la productivité

Cette partie rappelle la base légale, les caractéristiques et missions, ainsi que la composition du CNP.

3.
Le Conseil national de la productivité

Dans ce rapport annuel 2022-2023, le Conseil national de la productivité (CNP) se limite à rappeler brièvement sa base légale, ses caractéristiques et missions principales, ainsi que sa composition actuelle. Des informations plus détaillées et tous les rapports annuels du CNP sont disponibles sur la page Web du CNP[1].

3.1
Base légale du CNP

La base légale du CNP, à savoir l'arrêté grand-ducal du 23 septembre 2018 portant création d'un Conseil national de la productivité au Luxembourg, est restée inchangée[2].

3.2
Caractéristiques et missions du CNP

Le CNP bénéficie d'une autonomie fonctionnelle, ce qui lui permet de réaliser ses travaux de façon objective, neutre et impartiale, de produire des analyses formulées dans l'intérêt général et de communiquer publiquement en temps utile.

Le CNP est chargé de suivre les évolutions dans le domaine de la productivité en tenant compte des particularités nationales et des aspects liés à l'UE. Il est appelé à réaliser un diagnostic et une analyse de la productivité au Luxembourg en s'appuyant sur des indicateurs transparents et comparables. La portée des travaux englobe la productivité au sens large, y compris les facteurs coûts et hors coûts, les déterminants à long terme de la productivité ainsi que les défis et enjeux économiques, sociaux et environnementaux afférents.

3.3
Composition du CNP

Composition du Conseil national de la productivité (octobre 2023)

Président
M. Serge ALLEGREZZA,
Observatoire de la compétitivité

Vice-Présidents
M. Jean-Claude REDING,
Chambre des salariés

M. Michel WURTH,
ArcelorMittal Luxembourg

Membres
M. Arnaud BOURGAIN,
Université du Luxembourg

M. Patrick LENAIN,
Économiste

Mme Aline MULLER,
Luxembourg Institute of Socio-Economic Research

M. Marc NIEDERKORN,
Expert

Mme Chiara PERONI,
STATEC

M. Paul SCHOSSELER,
Ministère de l'Énergie et de l'Aménagement du territoire

Secrétariat
Observatoire de la compétitivité, Ministère de l'Économie

1 Page Web du CNP : https://odc.gouvernement.lu/fr/domaines-activite/cnp.html

2 Base légale du CNP : https://legilux.public.lu/eli/etat/leg/agd/2018/09/23/a951/jo

POUR DE PLUS AMPLES INFORMATIONS

CONSEIL NATIONAL DE LA PRODUCTIVITÉ
HTTPS://ODC.GOUVERNEMENT.LU/FR/DOMAINES-ACTIVITE/CNP.HTML

MINISTÈRE DE L'ÉCONOMIE
OBSERVATOIRE DE LA COMPÉTITIVITÉ
19-21 BOULEVARD ROYAL
L-2449 LUXEMBOURG
OBSERVATOIRE@ECO.ETAT.LU