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THE IMPACT OF INEQUALITY ON ACCUMULATION OF HUMAN CAPITAL AND ECONOMIC GROWTH

Dissertation thesis

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Declaration of Honour

I hereby solemnly declare that this thesis represents my own work and all sources used are listed in Bibliography

Bratislava, date ……… ……………………

Patrik Jankovič

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ABSTRACT

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Within country inequality has increased significantly since the 1970s with potentially negative impact on the present economies and their future development. This fact motivates us to introduce a new aspect of the nonparametric approach to the analysis of the interrelation between inequality, human capital accumulation, and economic growth already covered well by parametric approach literature. With the aim of finding how inequality may affect the accumulation of high skills, and later how high skills contribute to economic growth, we employ the data envelopment analysis (DEA) method. We use the advantage of DEA to construct the world production frontier, which is in turn used in two types of modified non-parametric decompositions. Compared to the parametric literature, the advantage of this approach allows us to differentiate the extra contribution of the movement towards the efficient frontier and the relative movement of a technological frontier shift to productivity change.

Firstly, we decompose productivity growth into components attributable to technological change (shift of the frontier), efficiency change (movements towards the frontier), physical capital deepening, and human capital accumulation in the form of high-skilled and low-skilled labour over the 1970-2010 period. We find our analysis in line with the findings of current parametric literature. Our results indicate a positive contribution of high skills to productivity growth on average. Furthermore, we conclude that the contribution of high-skilled labour to productivity growth had decreasing tendency for OECD countries, and an increasing importance for underdeveloped countries between 1970-1990 and 1990-2010.

Secondly, we decompose the change in the share of high-skilled labour into components attributable to technological shift, efficiency change, economic output, income inequality, and input mix over the last 40 years. We find that the contribution of inequality to high skills accumulation is negative for OECD countries between 1990-2010, while it has a slightly positive tendency during 1970-1990. The effect is ambiguous for underdeveloped countries with a rather positive tendency between 1990-2010.

Keywords: Economic Growth, Human Capital, Inequality, Data Envelopment Analysis, Nonparametric Decomposition

Abstrakt

JANKOVIČ, Patrik: Vplyv nerovností na akumuláciu ľudského kapitálu a na ekonomický rast. [Dizertačná práca]. – Ekonomická univerzita v Bratislave. Národohospodárska fakulta; Katedra hospodárskej politiky. – Školiteľ: Univ. prof. i. R. Dipl. Ing. Dr. Mikuláš Luptáčik – Bratislava: NHF EUBA, 2020. 141 s.

Ekonomická veda sa v posledných rokoch začala okrem veľkosti produktu zaoberať aj jeho distribúciou v populácii (Atkinson, 2015). Nedávne Svetové ekonomické fórum (WEF, 2020) zdôraznilo dôležitosť zaoberať sa rastúcou nerovnosťou ako jedným z hlavných svetových problémov súčasnosti. Zatiaľ čo nerovnosti medzi krajinami sa v posledných rokoch postupne zmenšovali, nerovnosti vo vnútri krajín rastú od sedemdesiatych rokov minulého storočia (Piketty, 2014). Keďže ľudia majú možnosť priamo porovnávať svoju situáciu s ostatnými členmi tej istej spoločnosti, nerovnosť vo vnútri krajiny je braná omnoho citlivejšie. Nerovnomerná distribúcia príjmov a bohatstva so sebou navyše prináša nebezpečenstvo jej prenosu medzi generáciami (Kearney and Levine, 2014). Tento proces spôsobuje následnú nerovnosť príležitostí s potenciálnymi konsekvenciami na motiváciu a rozhodovanie jednotlivcov o príprave na trh práce (OECD, 2015). Jedným z dôležitých kanálov je aj rozhodovanie sa jednotlivcov o najvyššom dosiahnutom vzdelaní. Vzdelanie, ako jedna z foriem ľudského kapitálu, je považované za motor rastu nie len rozvinutých ekonomík (Flabbi a Gatti, 2018). Ak je nerovnosť prenášaná medzi generáciami spôsobom, že si populácia v spodnej časti príjmovej distribúcie nemôže dovoliť vyššie vzdelanie, ekonomika prichádza o časť produktívneho faktoru. Keďže vzdelanie je na rozdiel od fyzického kapitálu neoddeliteľnou súčasťou jednotlivca, množstvo vzdelania, ktoré dokáže jednotlivec absorbovať je vo všeobecnosti obmedzené, a preto má výnos z pridaného roku vzdelania klesajúcu tendenciu (Weil, 2013). Preto ak jedna časť populácie vyššie vzdelanie nenadobudne, iná časť populácie túto stratu nevykompenzuje, ekonomika stráca svoj potenciál a rast produktivity je tak obmedzený (Galor and Zeira, 1993). Práve v tejto oblasti teórie o nerovnostiach má naša práca ambíciu prispieť do aktuálnej diskusie. Aplikáciou neparametrického intertemporálneho modelu prinášame nový pohľad na príspevok nerovností k akumulácií vyšších zručností a následný príspevok vyšších zručností k ekonomickému rastu.

Odpovedáme tým na otázky, ako prispieva nerovnosť k akumulácii ľudského kapitálu a ako následne ľudský kapitál k ekonomickému rastu.

Naša prvá hypotéza predpokladá negatívny príspevok nerovností k akumulácii vyššie vzdelanej práce, pričom ďalej predpokladáme negatívny výsledok najmä pre vzorku vyspelých krajín. Následne druhá hypotéza predpokladá pozitívny príspevok vyššie vzdelanej práce k rastu produktivity práce najmä vo vyspelých krajinách. Použitie neparametrického prístupu však môže priniesť aj dodatočné zistenia, ktoré síce nespadajú pod hlavné hypotézy dizertačnej práce, ale tvoria podstatnú časť jej prínosov. Prínosom sú najmä zistenia v oblasti príspevku posunu technologickej hranice či už k produktivite práce ale aj jej príspevku k akumulácii vyššie vzdelanej práce.

Literatúra, ktorá sa venuje problému nerovností sa v posledných rokoch dostala do centra nie len vedeckých diskusií. Knihy Thomasa Pikettyho (2014), Anthonyho Atkinsona (2015), alebo Branka Milanoviča (2016) poskytujú výnimočný pohľad do teórií nerovností a do nedávneho vedeckého výskumu pre široké masy. Ekonómovia sa zhodujú na rastúcom trende nerovností vo vnútri väčšiny krajín a najmä tých vyspelých (OECD, 2020). Preto otázka, či majú rastúce nerovnosti pozitívny alebo negatívny vplyv na ekonomický rast, naberá na dôležitosti viac ako kedykoľvek predtým. Diskusie na tému kauzality medzi týmito dvoma fenoménmi je nejednoznačná. Teoretické modely a empirický výskum prinášajú argumenty pre oba z týchto myšlienkových táborov.

Technologické a metodologické inovácie v ekonómii so sebou v posledných rokoch priniesli vznik mnohých kvalitných databáz so širokým záberom krajín a dostatočným historickým časovým radom. Zvýšenie kvality veľkých databáz a harmonizácia medzinárodných štatistík podnecujú ďalší ekonomický výskum. V našej dizertačnej práci využívame tri z takýchto databáz. Solt (2009) harmonizuje historické Gini indikátory naprieč svetovými krajinami, Lutz et al. (2008) poskytujú rozšírenú databázu o stupňoch vzdelania na základe spätnej projekcie dát podľa demografickej štruktúry obyvateľstva a v neposlednom rade Feenstra et al. (2015) zdokonaľujú Penn World Tables ako základ pre ekonomický výskum založený na historických údajoch.

Naša dizertačná práca má ambíciu prispieť do oblasti literatúry, ktorá sa zaoberá prepojením nerovností, akumulácie ľudského kapitálu a ekonomického rastu. Ekonomický výskum poskytuje veľké množstvo publikovaných analýz v každej z týchto dimenzií, pričom hlavným motívom je najmä prepojenie vývoja nerovností a ekonomického rastu. Nájsť systematické prepojenie medzi ekonomickým rastom a vývojom nerovností je v ekonomickom úsilí už od čias formulovania slávnej Kuznetsovej teórie (1955). Práve Kuznets verifikoval jeho teóriu na údajoch z obdobia industrializácie počas veľkej časti devätnásteho a dvadsiateho storočia. Jeho teória, podľa ktorej nerovnosť počas ekonomického vývoja sleduje krivku v tvare obráteného písmena U, kedy na začiatku industrializácie nerovnosti rastú a po dosiahnutí maxima opäť klesajú. Pokles nasledoval po technologických revolúciách medzi svetovými vojnami a sedemdesiatymi rokmi minulého storočia. Opätovný rast nerovnosti od sedemdesiatych rokov dvadsiateho storočia už však Kuznetsova teória vysvetliť nedokázala. To podnietilo vznik ďalších teórií o prepojení ekonomického rastu a nerovností, ktorými sa v práci zaoberáme.

Na začiatok skúmania témy o nerovnostiach je nutné vyjasniť si niekoľko zásadných otázok. Atkinson (2015) začína svoju úvahu o nerovnostiach otázkami: čo je to nerovnosť, nerovnosťou čoho sa zaoberať a naprieč akou vzorkou nerovnosť merať? Z týchto základných otázok sa odvíja interpretácia empirického výskumu, ale aj základné teoretické prístupy k nerovnostiam. Vo všeobecnosti by sme mohli nerovnosťou nazvať nerovnomernú distribúciu ľubovoľného objektu v ľubovoľnej populácii. Atkinson ďalej nerovnosti rozdeľuje v prvom rade na nerovnosti vo vstupoch a nerovnosti vo výstupoch. Výstupmi sú predovšetkým pojmy ako príjem, bohatstvo či produkcia. Vstupmi rozumieme okolnosti, ktoré vstupujú do procesu nadobúdania produktívnych faktorov, a ktoré následne determinujú ďalší príjem jednotlivca. Práve to, či má jednotlivec tieto faktory vo svojich rukách alebo nie, nás privádza k ďalšej dimenzii delenia nerovností a to podľa férovosti. Otázka férovosti je v súčasnosti veľmi aktuálna. Je tomu tak najmä vo vzťahu k sociálnej mobilite a pretrvávaniu nerovností naprieč generáciami (Kearney and Levine, 2014). Hufe et al. (2018) sa tejto téme venujú bližšie a spájajú dva aspekty neférových nerovností do jedného ukazovateľa. Spájajú nerovnosť príležitostí a slobodu od chudoby do zjednoteného indikátora neférových nerovností. Zisťujú napríklad, že rastúce nerovnosti v Spojených štátoch boli medzi rokmi 1980-1990 ťahané prevažne férovou nerovnosťou, no od roku 1990 je možno považovať väčšiu časť prírastku v nerovnostiach za neférovú. Preto je podľa nich potrebné rozlišovať typy nerovností a ich pozitívne a negatívne dopady. Nanešťastie naša dizertačná práca neprekračuje úroveň základných ukazovateľov nerovností, ale naša motivácia a interpretácia výsledkov sa zakladá na podobných princípoch.

Teória Galora a Moava (2004) prepája časť teórií o nerovnostiach s modelmi ekonomického rastu a s významom vzdelania v tomto procese. Tak ako zhrnul Milanovič (2015), vývoj ekonomík nie je opísaný jedinou Kuznetsovou krivkou, ale vystihuje ho skôr niekoľko takýchto kriviek, ktoré vytvárajú vlnenie. Každá takéto vlna opisuje ďalšiu technologickú revolúciu a nerovnosti zodpovedajú konkrétnej fáze. Týmto prichádzame k hypotéze, že svetová ekonomika sa od sedemdesiatych rokov minulého storočia nachádza na počiatku novej technologickej fázy a to je príčinou rastúcich nerovností.

Rolu ľudského kapitálu v tomto procese vystihuje práca Goldin a Katz (2009), ktorí opisujú vývoj mzdovej prémie naprieč dvadsiatym storočím ako preteky medzi vzdelaním a technológiou. Mzdová prémia vo vyspelých krajinách s rastúcou ponukou vzdelaných v prvej polovici dvadsiateho storočia klesala, ale v druhej polovici opäť rastie s príchodom nových technológií. Inšpirujúc sa prácou Beckera (1962), autori rozoberajú aj motiváciu vzdelávať sa v jednotlivých fázach ekonomického progresu. Opierajú sa o fakt, že vznik a šírenie novej technológie je podmienené rozšírením potrebných zručností v ekonomike. A práve relatívna cena medzi starými a novými zručnosťami má rozhodovať o relatívnej cene práce a jej nerovnomernej distribúcii aj v súčasnej dobe (Caselli, 1999). Podobný princíp, relatívnych cien ale medzi fyzickým kapitálom a prácou opisuje aj model Galora a Moava (2004). Ich model ekonomického vývoja v dlhom období vysvetľuje súčasný trend narastajúcich nerovností od 1970. Autori vychádzajú zo základných predpokladov rastúceho hraničného sklonu k úsporám, ktorý pri prehlbovaní nerovností vedie k rastúcim agregátnym úsporám a investíciám. Model ďalej predpokladá nedokonalostí úverového trhu, kedy obmedzenia na tomto trhu vedú k obmedzeným možnostiam chudobných investovať do ľudského kapitálu a na predpoklade komplementarity medzi fyzickým a ľudským kapitálom, kedy akumulácia fyzického kapitálu vedie k rastu dopytu po kvalifikovanej ľudskej práci a teda k akumulácii ľudského kapitálu. Autori opisujú začiatok industrializácie ako obdobie, kedy bol motorom rastu fyzický kapitál, ktorý si vyžadoval koncentráciu úspor a preto bola rastúca nerovnosť prospešná pre ekonomický rast. Počas dvadsiateho storočia si ale vysoká zásoba fyzického kapitálu vyžadovala rast kvalifikovanej pracovnej sily, ktorá sa stala novým motorom rastu (Flabbi a Gatti, 2018). Počas fázy, kedy je ekonomický rast ťahaný ľudským kapitálom (Mankiw et al., 1992), je podľa teórie Galora a Moava (2004) nerovnosť nežiaduca. Dôvodom prečo je v tejto fáze nerovnosť neželaná vysvetľuje Galor a Zeira (1993) teóriou nedokonalých úverových trhov. Ich medzigeneračný model je založený na nedokonalostiach úverového trhu, nedeliteľnosti ľudského kapitálu, nekonvexite technologického pokroku a nerovnomernej distribúcii dedičstva. Predpoklad nerovnej distribúcie dedičstva spôsobuje, že pre chudobných (bez dedičstva) je požičiavanie si na úverovom trhu nákladnejšie, a preto jednotlivci bez dedičstva nemajú možnosť investovať do produktívnych faktorov akými je vzdelanie (Becker, 1975). Už Loury (1981) upozorňoval na fakt, že nedeliteľný ľudský kapitál spôsobuje jeho obmedzenú zásobu na jednotlivca a nerovný prístup ku vzdelaniu znižuje jeho agregovanú výšku v spoločnosti.

Závery súčasnej literatúry konvergujú práve k podpore názoru, že kanál, ktorým nerovnosť neblaho vplýva na ekonomický rast, najmä v rozvinutých krajinách, je cez akumuláciu ľudského kapitálu za podmienok nedokonalého úverového trhu (OECD, 2015; Halter et al., 2014; Brueckner and Lederman, 2018; Ostry et al., 2018). Tieto teórie sa zakladajú na endogenite ekonomického rastu, kedy produktivita práce a technologický pokrok závisia práve od investícií do vzdelania (Romer, 1986, LUCAS, 1988). Ak totiž systematické medzigeneračné pretrvávanie nerovného prístupu k zdrojom pretrváva a zároveň je talent rozdelený náhodne, ekonomika zákonite prichádza o časť svojho potenciálu. OECD (2015) prináša hmatateľné dôkazy o tom, že deti v spodných častiach distribúcie príjmov dosahujú signifikantne nižšiu úroveň najvyššieho dosiahnutého vzdelania a zároveň dosahujú horšie skóre v medzinárodnom testovaní PIAAC. Autori tým dokazujú predpoklad, že sociálne postavenie rodičov pretrváva a determinuje tak budúci príjem ich detí. Jedinci preto nemajú svoj budúci príjem vo svojich rukách a ako poukázali Hufe et al. (2018), obmedzená sociálna mobilita znižuje férovosť nerovností a prispieva k ich prehlbovaniu naprieč generáciami (Hassler et al., 2007).

Ďalej, Brueckner a Lederman (2018) aplikujú teóriu Galora a Zeira (1993) na panelových dátach. Medzi rokmi 1970-2010 za použitia inštrumentálnych premenných, ktorými odstraňujú endogenitu najmä ľudského kapitálu zisťujú, že zvýšená nerovnosť prispieva k ekonomickému rastu pozitívne v krajinách s nižšou úrovňou počiatočného príjmu na obyvateľa. Naopak negatívny efekt nerovností na ekonomický rast cez akumuláciu vyššieho vzdelania nachádzajú vo vyspelých krajinách.

Nedávny príspevok OECD (2015) sa zaoberá prenosom nerovností medzi generáciami, čím priamo prispieva k obmedzeným možnostiam vzdelávania nízkopríjmových skupín obyvateľstva vo vyspelých krajinách. Analýza na úrovni individuálnych dát obohatená o rozmer testovania zručností PIAAC očisťuje vzťah medzi nedostatkom vyplývajúcim z nerovnej distribúcie zdrojov a príležitostí v spoločnosti a produktivitou jednotlivca odvodenej od jeho vzdelania. Zakomponovaním proxy zložky vzdelania a príjmu rodičov autori poodhaľujú kauzálny vplyv medzi nerovnosťou v spodnej časti distribúcie a stratou ľudského kapitálu a jeho budúcej produktivity. Podporujú tým záver, že sociálna mobilita, a teda nerovnosť v spodnej časti distribúcie (približne spodných 40% distribúcie), je kľúčová pre ekonomický rast vyspelých krajín.

Ambíciou našej dizertačnej práce je priniesť do témy vzájomného vzťahu medzi nerovnosťami, akumuláciou ľudského kapitálu a ekonomickým rastom neparametrický pohľad, ktorý je založený predovšetkým na definovaní efektívnej technologickej hranice a relatívnej vzdialenosti krajiny od nej. Definovanie efektívnej hranice je hlavou výhodou analýzy dátového obalu (Data envelopment analysis – DEA) oproti parametrickým – ekonometrickým prístupom. Luptáčik a Mahlberg (2011) definujú dva prístupy k analýze produktivity. Parametrický, teda neoklasický, a aj neparametrický prístup efektívnej hranice mapujú produktivitu ako podiel výstupov a vstupov ekonomiky. Líšia sa však v použitých metódach. Neoklasický prístup pripisuje príspevky k rastu produktivity faktorom, ale nedokáže rozlíšiť medzi pohybom krajiny voči efektívnej hranici a nepozoruje ani pohyb tejto hranice. Neparametrický prístup dokáže rozložiť rast produktivity na príspevok medzi relatívny pohyb krajiny k efektívnej hranici a samotného pohybu hranice. Podstata oboch prístupov je zobrazená na Obrázku 6.1, ktorý opisuje hodnotenie produktivity v prípade jedného vstupu a jedného výstupu. Parametrický prístup reprezentuje jednoduchý lineárny odhad metódou najmenších štvorcov (OLS) a parametrický prístup obaľuje dáta hranicou tvorenou z krajín, ktoré boli vyhodnotené ako efektívne. V OLS minimalizáciou štvorcov odchýlok hľadáme najlepšie parametre, ktoré definujú funkciu vystihujúcu spoločnú technológiu krajín v podobe priamky alebo krivky cez zhluk bodov. Priamka minimalizuje štvorce odchýlok od pôvodných dát.

V prípade neparametrického prístupu metódou DEA, maximalizujeme podiel virtuálneho výstupu a virtuálneho vstupu na základe voľby optimálnych váh. V DEA analýze krajinu označujeme ako samostatne sa rozhodujúcu jednotku (DMU – Decision making unit), ktorej technológia sa obyčajne skladá z niekoľkých výstupov a niekoľkých vstupov, alebo inými slovami z vektora výstupov a vektora vstupov. Virtuálny výstup je preto sumou vektora výstupov váženého prislúchajúcimi váhami a v prípade virtuálneho vstupu je to vektor vstupov vážený prislúchajúcimi váhami vstupov. Váhy si vyberáme tak, aby sme maximalizovali podiel sumy vážených výstupov k sume vážených vstupov. Vybrať si váhy, ktoré budú maximalizovať konkrétne náš podiel nie je zložitá úloha. Na druhej strane sa situácia komplikuje, keď si svoje váhy vyberá niekoľko odlišných jednotiek DMU. K podstate DEA analýzy sa dostávame, keď necháme jednotky DMU v počte n vybrať si váhy tak, aby bola hodnota ich podielu virtuálnych výstupov a virtuálnych vstupov relatívne vyššia ako ostatných jednotiek DMU (Luptáčik, 2010). Tie jednotky DMU, ktoré v istej konfigurácii váh dosahujú najvyššie skóre, budú efektívne s hodnotou efektívnosti 1 a skóre ostatných bude vypočítané relatívne ku vzorovej jednotke DMU s efektívnosťou medzi 0 a 1.

K podstate prístupu, ktorým sa zaoberáme v dizertačnej práci sa dostaneme, keď si predstavíme pohyb efektívnej hranice v čase, so súčasným pohybom konkrétnej jednotky DMU smerom k alebo od, či už pôvodnej alebo novej efektívnej obálky. Vyššie uvedenú jednoduchú medzi-časovú analýzu nazývame Malmquistov index (Cooper et al., 2007). V našej práci sa budeme ďalej zaoberať dvoma prípadmi medzi-časovej neparametrickej dekompozície, ktoré rozoznávajú nie len pohyb hranice a relatívny pohyb ku hranici, ale aj pohyb pozdĺž efektívnej obálky. Pohyb pozdĺž hranice sa dá rozdeliť na príspevok spôsobený zmenou vstupov a zmenou výstupov. Konkrétne, v prvom kroku modifikujeme neparametrickú dekompozíciu podľa Hendersona a Russella (2005) a v druhom kroku našej analýzy modifikujeme prístup Färe et al. (2018).

Cieľom našej dizertačnej práce je s využitím medzi-časovej neparametrickej dekompozície v prvom kroku zistiť príspevok nerovností k kumulácii ľudského kapitálu v podobe vyššie vzdelanej pracovnej sily a následne v druhom kroku zisťujeme príspevok vyššie vzdelanej pracovnej sily na rast produktivity v období 1970-1990-2010. V prvom kroku rozkladáme zmenu v akumulácii vyššie vzdelaných na príspevok posunu efektívnej technologickej hranice, relatívneho posunu krajiny k tejto hranici, efekt nerovností, príspevok zmeny hrubého domáceho produktu a zmeny vstupov v podobe nižšie vzdelanej práce a zásoby kapitálu. V druhom kroku rozkladáme zmenu v produktivite na príspevky posunu efektívnej hranice, posunu krajiny k alebo od tejto hranice, príspevok zmeny kapitálovej zásoby, efekt vyššie a nižšie vzdelanej práce.

Keďže si medzi-časová neparametrická dekompozícia vyžaduje balansovaný, respektíve úplný panel dát, pre našu analýzu potrebujeme kompletné údaje pre každý z prierezov 1970, 1990 a 2010. Tento fakt nám spôsobuje značné komplikácie kvôli nedostatku dostupných dát. Preto uskutočňujeme analýzu na viacerých vzorkách krajín podľa dostupnosti časového radu pre odlišnú technológiu v prvom a druhom kroku analýzy. Vstupy použité v technológii pre dekompozíciu sú kapitálová zásoba v stálych cenách a parite kúpnej sily (Feenstra et al. 2015) spolu s vyššie a nižšie vzdelanou zásobou pracovníkov. Premenné vyššie a nižšie vzdelanej práce dostávame pomocou databázy odhadnutej spätnou projekciou vzdelanostných skupín podľa demografických charakteristík obyvateľstva spätne až do roku 1960 pre širokú vzorku krajín (Lutz et al., 2018). Ako vyššie vzdelanú prácu definujeme aktívnu populáciu so sekundárnym a vyšším vzdelaním vo veku 16-64 rokov upravenú o priemernú mieru zamestnanosti v danom roku a krajine. Podiel vyššie a nižšie vzdelanej práce na aktívnej populácii preto nie je rovný jednej a existuje potenciál zapojenia ďalších pracovných síl aj bez nutnosti medzištátnej pracovnej migrácie. Výstupom našej technológie je hrubý domáci produkt v stálych cenách a parite kúpnej sily.

V prvom kroku, pri dekompozícii vplyvov na ľudský kapitál vkladáme do technológie navyše takzvaný neželaný výstup v podobe Giniho indexu (Solt, 2019). Negatívny výstup znamená, že vyššia nerovnosť prispieva k hodnoteniu efektívnosti negatívne, ale v podiele virtuálneho výstupu k virtuálnemu vstupu sa príjmová nerovnosť nachádza v čitateli. Nerovnosť považujeme v tomto prípade za výstup podľa funkcie spoločenského blahobytu, kedy sa pozeráme nie len na želanú výšku výstupu, ale aj na nerovnosť, ktorá znižuje úroveň spoločenského blahobytu (Nikola, 2013, Fleurbaey, 2009). V prípade merania nerovností priznávame, že jednoduchý Giniho index nemusí zachytiť všetky zmeny v distribúcii, ale vzhľadom k šírke historických dát, ktoré sa pokúšame obsiahnuť v našej analýze, ide o jediný ukazovateľ nerovnosti siahajúci do roku 1970.

Ako sme spomínali, zostrojiť kompletný panel krajín s premennými hrubého domáceho produktu, kapitálovej zásoby, zásoby nižšie a vyššie kvalifikovanej práce a v prípade prvého kroku dekompozície aj údaje pre Giniho index za roky 1970-1990-2010, je pomerne náročné. Pre aplikáciu našej metodológie si vyberáme 3 typy panelu. Dataset „33“ je vzorkou 33 krajín, z ktorých 16 je členom OECD, preto nemožno hovoriť o vzorke reprezentujúcej svetové krajiny, ale na druhej strane je konzistentná naprieč rokmi 1970-1990-2010. Ďalšou vzorkou je dataset „79“, kde sa zbavujeme klasických „outlier“ krajín ako LDC krajiny, malé mestské štáty či takzvané ropné štáty, ktoré zvyknú nežiaduco ovplyvňovať efektívnu hranicu. Vzorka 79 krajín je konzistentná medzi obdobiami 1990-2010. Posledná vzorka 161 krajín konzistentná medzi rokmi 1990-2010 je určená výhradne druhému kroku našej analýzy, lebo vzorka obsahuje aj krajiny bez údajov o nerovnosti. Vo vzorke „161“ preto zisťujeme iba príspevok vyššieho vzdelania na produktivitu krajiny.

V praktickej časti sa zameriavame na dva kroky. V prvom kroku využijeme modifikovanú neparametrickú medzi-časovú dekompozíciu podľa Färe et al. (2018) (ďalej ako FR) na to, aby sme odhalili príspevok nerovnosti na akumuláciu vyššieho vzdelania na paneloch „33“ a „79“. Následne, v druhom kroku praktickej časti používame modifikovanú metodológiu podľa Hendersona a Russella (2005) (ďalej ako HR) pre určenie príspevku zásoby vyššie vzdelanej pracovnej sily na rast produktivity. Výsledky za jednotlivé krajiny uverejňujeme v prílohe, pri prezentácií výsledkov sa zameriavame na porovnanie distribúcie jednotlivých príspevkov a porovnávame ich rozdelenie podľa času a ekonomickej vyspelosti krajín. Krajiny rozdeľujeme na vyspelé, členské krajiny OECD, rozvojové krajiny v skupine krajín LDC a zvyšné krajiny označujeme pojmom „ostatné“ krajiny.

V prvom kroku zisťujeme, že aplikáciou FR dekompozície na panel „33“ a „79“ na prvý pohľad nenachádzame výrazný príspevok nerovností k akumulácii vyššieho vzdelania pracovníkov. Na celkovej vzorke sa vplyv nerovností relatívne stráca. Je to spôsobené tým, že nerovnosti sa v čase nemenia tak výrazne ako ostatné faktory. Zvlášť Giniho index nie je schopný zachytiť každý pohyb v celkovej distribúcii príjmov. Ďalej sa na výsledky pozeráme podrobnejšie a nachádzame, síce malý, ale systematický vzťah medzi nerovnosťou a akumuláciou vyššieho vzdelania v krajine.

Berúc do úvahy príspevok posunu efektívnej hranice, pohybu krajiny smerom k efektívnemu obalu, príspevok zmeny hrubého domáceho produktu a zmeny vstupov v podobe kapitálovej zásoby a nižšie vzdelanej práce, nachádzame medzi zmenou nerovností a ich príspevkom k akumulácii vyššie vzdelanej pracovnej sily jasnú previazanosť. Ak sa nerovnosť v krajine zvýšila, príspevok k akumulácii vyššie vzdelaných bol negatívny (menší ako 1) alebo žiaden (rovný 1). Na druhej strane, ak nerovnosť v krajine poklesla, jej príspevok bol buď neutrálny (rovný 1) alebo pozitívny (väčší ako 1). Je tomu tak v každej z troch FR dekompozícií. Tento záver prispieva k tvrdeniam o negatívnom vzťahu medzi nerovnosťami a akumuláciou kapitálu (Galor and Zeira, 1993).

Ďalším zaujímavým výsledkom je rôzna distribúcia príspevku nerovností k akumulácii vyššie vzdelaných pracovníkov medzi rozvinutými OECD krajinami a „ostatnými krajinami". Medzi rokmi 1970-1990 krajiny OECD vykazujú mierne pozitívny príspevok nerovností k akumulácii vyššie vzdelaných, zatiaľ čo výsledky menej rozvinutých regiónov nie sú odlišné od hodnoty 1 naznačujúca žiaden efekt. Následne medzi rokmi 1990-2010 na vzorke „33" aj na vzorke „79" zisťujeme, že výsledok je v prípade rozvinutých krajín negatívny a v prípade ostatných krajín prevažne pozitívny. Tieto výsledky podporujú aj závery nedávnych parametrických modelov. Model Galora a Moava (2004) či aplikácia teórie Galora a Zeira (1993) analýzou Bruecknera a Ledermana (2018) podporujú tvrdenie, že v krajinách s nižším stupňom rozvoja môže nerovnosť prispievať k ekonomickému rastu ak je motorom rozvoja akumulácia fyzického kapitálu. V súčasných rozvinutých krajinách, kde je motorom ekonomického rastu ľudský kapitál, prispieva nerovnosť k rastu hrubého domáceho produktu negatívne cez kanál obmedzenej akumulácie vyššieho vzdelania.

Ak predpokladáme, že výsledok vplyvu nerovností sa na akumulácii vyššieho vzdelania prejaví s oneskorením, naše výsledky naznačujú pozitívny vplyv nerovností na akumuláciu vyššieho vzdelania. 20 rokov oneskorený vplyv nerovností overujeme na vzorke „33", kedy v roku 1990 používame údaje o Giniho indexe z roku 1970 a pre prierez v roku 2010 používame nerovnosť spred 20 rokov. Výsledky porovnávame s dekompozíciou medzi rokmi 1990-2010 a zisťujeme, že v prípade menej rozvinutých krajín sa pozitívny príspevok nerovností znižuje, a v prípade krajín OECD sa dostávame z negatívnych čísel k pozitívnemu príspevku k akumulácii vyššie vzdelaných pracovníkov. Ide však o nereprezentatívnu vzorku 33 krajín a oneskorenie vplyvu nerovností, ktoré by sa malo prejaviť v detstve (OECD, 2015) sa môže líšiť naprieč krajinami podľa priemernej dĺžky vzdelania.

V druhom kroku našej práce pomocou HR dekompozície potvrdzujeme pozitívny vplyv vyššieho vzdelania na ekonomickú produktivitu krajín. Zaujímavým je v tomto prípade rozdelenie krajín podľa stupňa vyspelosti a distribúcia príspevku vyššie vzdelaných pracovníkov či posunu technologickej hranice. V tejto časti konkrétne zisťujeme príspevok vyššie vzdelanej pracovnej sily na ekonomickú produktivity berúc do úvahy príspevok posunu efektívnej hranice, pohybu krajiny smerom k efektívnemu obalu a efekt zmeny vstupov v podobe kapitálovej zásoby a nižšie vzdelanej práce. Naša práca obsahuje 4 HR dekompozície. Dve dekompozície zachytávajú obdobie medzi rokmi 1970-1990-2010 na vzorke „33“ a po jednej dekompozícii sledujeme na vzorke „79“ a „161“ obdobie medzi rokmi 1990-2010.

Dekompozície medzi rokmi 1970-1990 a 1990-2010 na vzorke „33“ poukazujú na pozitívny ale klesajúci príspevok vyššie vzdelanej pracovnej sily k rastu produktivity práce v rozvinutých krajinách a pozitívny rastúci príspevok v prípade menej rozvinutých krajín. Zatiaľ čo medzi rokmi 1970-1990 prispievala vyššie vzdelaná práca len minimálne k produktivite v menej rozvinutých krajinách, v období medzi rokmi 1990-2010 bol už v ich prípade príspevok vyšší ako vo vzorke krajín OECD. Náš výsledok dokazuje, že vyššie vzdelanie sa v súčasnosti stáva motorom ekonomického rastu pre menej rozvinuté krajiny, keďže kvantita vzdelanosti už narazil na svoju hranicu vo väčšine vyspelého sveta.

Rozdiel v príspevku vyššie vzdelaných podľa vyspelosti krajín je lepšie vidieť na vzorke „161“. Vzorku rozdeľujeme podľa vyspelosti na 3 skupiny, konkrétne na vyspelé krajiny OECD, „ostatné“ krajiny a najmenej rozvinuté krajiny LDC. Zisťujeme, že medzi rokmi 1990-2010 prispela zmena v zásobe vyššie vzdelanej práce najviac v prípade najmenej rozvinutých krajín, o niečo nižšie boli výsledky „ostatných“ krajín a najmenší, ale stále pozitívny príspevok sme zaznamenali v prípade krajín OECD. Tieto výsledky dokazujú, že motorom ekonomického rastu v podobe sekundárneho a terciárneho vzdelania je v súčasnosti najvýraznejší v najmenej rozvinutých krajinách.

Odpoveď na otázku, ktorá sa automaticky žiada, čo je motorom ekonomického rastu vo vyspelých krajinách. Odpoveď na túto otázku nachádzame v ostatných faktoroch našej dekompozície, konkrétne v príspevku posunu technologickej hranice. Ak sa zameriame na príspevok technologickej hranice na ekonomickú produktivitu krajín, zisťujeme, že jeho príspevok je prirodzene pozitívny. Dôležitejšie zistenie ale je, že omnoho výraznejší príspevok technologického pokroku nachádzame vo vyspelých krajinách. Na vzorke „161“ je to zreteľné. LDC krajiny dosahujú nízke hodnoty príspevku technologického pokroku k rastu produktivity, „ostatné“ krajiny vyšší s veľkým rozptylom a OECD krajiny dosahujú najvyššie výsledky príspevku technologického pokroku k rastu produktivity práce.

Na záver, zaujímavou črtou v prvom kroku našej dekompozície je neintuitívny negatívny príspevok posunu technologickej hranice na akumuláciu vyššie vzdelanej pracovnej sily. Tento výsledok totiž naznačuje, že technologický pokrok znižuje množstvo vyššie vzdelanej pracovnej sily. Vysvetliť si tento výsledok je nutné v spojení so záverom predchádzajúceho odstavca, a teda že technologický pokrok prispieva k rastu produktivity práce. Ak totiž pokrok prispieva k produktivite práce, je prirodzené, že pri zvýšenej produktivite sa potreba pracovnej sily vo všeobecnosti znižuje. Naša dekompozícia preto poukazuje aj na to, že negatívny vplyv posunu technológie na vzdelanú prácu je výraznejší vo vyspelejších krajinách, kde je príspevok technológie k produktivite práce vyšší.

Kľúčové slová: ekonomický rast, ľudský kapitál, nerovnosť, analýza dátového obalu, neparametrická dekompozícia

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1 Introduction

Recently, the World Economic Forum has emphasized the urgency to deal with increasing inequality as one of the main global issues. While the inequality between countries has decreased in recent years, the within-country inequality has had a significantly increasing tendency since the 1970s. Within the country, inequality is treated more sensitively because people in the same society can directly compare their situation with others. Disproportions in the distribution of income or wealth brings a serious risk of their persistence over generations through the inequality of opportunities with potentially serious consequences on economic growth.

Inequality literature is not only in the centre of scientific discussions. Books by Thomas Piketty (2014), Anthony Atkinson (2015), or Branko Milanovic (2016) provide comprehensive insights into inequality theories and the recent scientific research for broad masses.

The question of whether inequality has a positive or a negative impact on economic progress is now more important than ever before. Research into the interrelation between inequality and economic growth is often ambiguous. There is a continuous discussion about the direction of causality between two phenomena and both arguments are well supported by theoretical concepts and empirical studies.

Fortunately, the broad coverage of data has further improved significantly in recent decades. Improvements in the quality and harmonization of indicators allow for the construction of big datasets that encourage advanced scientific research. The Standardized World Inequality Database (SWIID) by Solt (2009) summarizes inequality measures. Lutz et al. (2008) provides extended education attainment statistics, or the still-improving source of aggregate economic data, the Penn World Tables (PWT) (Feenstra et al., 2015), provide a solid ground for the verification of new hypotheses and empirical research.

This dissertation thesis aims to contribute into the literature focused on linkages between inequality, human capital formation, and the growth of economic output. Since the famous Kuznets theory (1955), there have been great efforts to find a systematic relation between economic growth and the level of inequality. Kuznets validates his theory about inequality progress during economic development phases on available historical data sets from the 19th and most of the 20th century. Unfortunately, the Kuznets curve is not able to sufficiently explain the phenomenon of increasing inequality since the 1970s. This fact stimulated a new stream of inequality literature trying to explain the processes of the last decades. We summarize most of the inequality literature in Chapter 4.

This dissertation is inspired by the literature related to Galor and Moav (2004), who formulated a model explaining economic processes over the long run, which seems to be valid also for recent decades. Their explanation is based on the relative rate of return between human capital and physical capital. They find that physical capital is scarce in the early stages of industrialization, so the rate of return to human capital is lower than the rate of return to physical capital. The process of development is fuelled by physical capital accumulation in the early period. On the other hand, in the later modern development phase, like after the 1970s, the human capital emerges as a growth engine with an increasing rate of return relative to physical capital. Therefore, if inequality harmed the accumulation of human capital, it would inhibit economic growth as well. Later, our analysis is also inspired by the literature providing evidence for the importance of human capital formation in the form of education as a positive determinant of development. Most of this literature is based on the endogenous model by Lucas (1988) or Romer (1990) and the contribution of Mankiw, Romer, and Weil (1992) to the Solow model (1956).

The theory of human capital, which started with the pioneering work of Schultz (1961) and Becker (1962), plays an important role in the formulation of the model by Galor and Zeira (1993). Their general equilibrium model with overlapping generation under the condition of imperfect capital markets describes the relationship between the accumulation of human capital and income or wealth inequality. They argued that income distribution influences macroeconomic statistics through unequal investments in human capital. The theory of Galor and Zeira (1993) has common foundations with the literature dedicated to the persistence of inequality over generations, also known as the social mobility issue (Kearney and Levine, 2014). The literature provides more alternative models supporting the idea that greater inequality might reduce economic growth. Recent findings of OECD (2015) show that the effect of reduced investments to education may cause significant loss of human capital with more serious effects among developed countries. These findings are supported by Voitchovsky (2005), who found that inequality at the top of the distribution is positively related and inequality at the bottom of the distribution is negatively related to economic growth. This hypothesis was later supported by the interesting contribution of Huffe et al. (2018) into the topic of unfair inequality. The theory of imperfect capital markets implies that individuals with lower wealth, income, or social background have reduced or more expensive (loan) possibilities to afford worthwhile investments in education (Galor and Zeira, 1993). In such an environment, lower parts of the distribution, mainly the poor, are disqualified from getting education corresponding to their potential, and so the economy loses potential talents and productive factors.

Different streams of literature seem to be linked in some points with Galor and Moav's theory (2004). The human capital rate of return increased proportionally to physical capital since 1970, and the importance of skilled labour increased in the development process according to the economic growth literature review by Flabbi and Gatti (2018). What is more, regarding the income divide between skilled labour groups, the relative quantity of high-skilled labour has increased substantially, and the skill premium, which is the wage for high-skilled labour relative to that for low-skilled labour, has grown significantly since 1980. Krusell et al. (2000) claim that under the capital-skill complementarity, changes in observed inputs alone can account for most of the variations in the skill premium over the last 30 years. Skill-biased technological progress favours high-skilled labour in novel industries, when the skill-biased revolution triggers reallocations of capital from slow- to fast- learning workers, thereby reducing the relative wages of employees from old industries (Caselli, 1999). Moreover, an increase in the rate of technological progress raises the return to ability and simultaneously generates wage inequality between high-skilled and low-skilled workers (Goldin and Katz, 2009). Consequently, income inequality research expresses a concern about increasing inequalities, which could potentially inhibit economic growth through low equality of opportunities transmitted to the next- generation (Atkinson, 2015). The accumulation of human capital among the lower parts of the distribution is reduced with potentially negative consequences on economic growth (Voitchovsky, 2005). Recently, Lankisch et al. (2019) provide evidence in favour of the fact that automation is related to increasing output per capita, declining real wages of low-skilled workers, and rising wage premium for higher education on empirical evidence from the United States since the 1970s. They also provide immediate policy conclusions based on an empirical study that investments in higher education can help to soften the negative effects of automation.

Literature already provides several approaches and a number of robust results about the interrelation between inequality, human capital, and economic growth. We contribute to the present state of the art by introducing advantageous features of the nonparametric approach into this debate. The nonparametric approach provides, in comparison to the previous methodology, the advantage of identifying of the world technological frontier under the multiple outputs and multiple input technology setting. Another advantage is the decomposition of a relative intertemporal efficiency change of a country into the contribution of the technological frontier shift and the contribution of the movement towards the frontier. We base this dissertation methodology on the work of Henderson and Russell (2005) and Färe et al. (2018). Both take advantage of a technical efficient frontier construction typical for non-parametric methods based on the data envelopment analysis model. Data envelopment analysis intertemporal decomposition allows us to decompose productivity growth into the movement of the economy towards the technology frontier and the shift of the frontier with ascribing productivity growth contribution to inputs and outputs of the individual economy (Luptáčik and Mahlberg, 2011).

This dissertation aims to contribute to the existing literature in two ways. In the first step, we modify the nonparametric decomposition by Henderson and Russell (2005). The modification of their model is based on the use of labour with high- and low- skills instead of labour augmented by human capital (Hall and Jones, 1999). By doing so, we partly avoid the discussion about the reliability of education quality while using the average years of schooling. An internationally standardized scale of educational levels provides an education measure comparable between countries, which was demographically back-projected by Lutz et al. (2008) back to 1960 for a wide range of countries. Our motivation to modify the educational measure comes from the research by Lutz et al. (2008) or Flabbi and Gatti (2018), who base their analysis of economic growth on detailed data about the level of education instead of Mincerian returns to education. Using the recent dataset of Lutz et al. (2018) we find that the contribution of high- and low- skilled labour to productivity growth. Secondly, we employ the modified nonparametric decomposition by Färe et al. (2018) to analyse the process of human capital accumulation. The reason to modify this method is to reveal the contribution of increasing inequalities to the accumulation of human capital. This idea is inspired by the theory of Galor and Zeira (1993), who argue that in imperfect capital markets, increasing inequality decreases investment in education because a smaller fraction of the population can afford to educate their children. Thus, in this situation, higher inequality hampers the accumulation of human capital, which could have detrimental effects on economic growth.

This dissertation thesis is composed of 8 chapters. Chapter 2 is dedicated to the description of the recent development of inequality, the theoretical concepts of inequality, and an alternative measurement of inequality. Chapter 3 shortly characterizes simple economic growth approaches and the importance of human capital formation for economic development. Chapter 4 reviews the literature on the possible relationship between inequality and economic growth. The Chapter 5 is dedicated to the main aim of our research. Later, the nonparametric methodology is explained in Chapter 6. We gradually introduce simple models and explain the principles and our modifications of intertemporal decompositions by Henderson and Russell (2005) and Färe et al. (2018). Chapter 7 presents our empirical results from three different panels covering the period between 1970-2010. And finally, the last chapter concludes our findings and discusses possible improvements and future research challenges.

2 Economic inequalities

As Atkinson (2015) quotes in his recent book "beyond the average level of income economists are interested in inequalities". Distribution of income among the country population has attracted attention for a long time, but only in the last decade, this issue started to be treated with serious concerns. While the income inequality between countries seems to diminish gradually, the gap between rich and poor within countries has deepened since the 1970s (Atkinson, 2015). Naturally, within-country inequality is treated more sensitively than the one between countries. Inequality within-country leads to consequences which can be easily observed in citizens' personal stories. People derive their happiness not from the absolute level of their consumption but from how their consumption compares with that of the people around them (Weil, 2013). That is why the increase in within-country inequality attracts so much attention.

To start a debate about the issue of inequality, it is important to admit that the reason why income inequality exists is derived from differences in our basic characteristics so that there does exist fair and unfair inequalities. It is natural that if two individuals differ in productivity of their work, they will differ also in income and wealth (Weil, 2013). If they differ solely in their inborn abilities, people are unequal in economic point of view fairly. On the other hand, if your income is determined by your social background, there is unfair inequality. It is unfair if the starting point which disqualifies individuals to get productive factors is distributed unequally (Atkinson, 2015). Inequality of opportunities use to persist over generations and reduces social mobility (Kearney and Levine, 2014). On the other hand, Piketty (2014) argues that outcome inequalities are both necessary to incentivize individuals and may comply with the requirements of justice in a market economy (Piketty, 2014).

Along the philosophical theories of distributive justice differentiate between fair (justifiable) and unfair (unjustifiable) inequalities. A very recent contribution to this stream of literature provides Hufe et al. (2018), who define the measure of unfair inequality by reconciling two prominent fairness principles, namely equality of opportunity and freedom from poverty into the joint measure. Their work highlights that we should be concerned not about inequalities in outcomes per se, but that we should rather focus on the sources of outcome inequalities. Unfair sources of inequality shall be eliminated completely while fair inequalities ought to persist. So that eliminated shall be unfair inequalities rooted in factors beyond an individual control like limited social mobility, gender pay gap, or racial disparities. Hufe et al. (2018) provide two empirical applications. Firstly, they find that unfair inequality doubles when complementing the concern for unequal opportunities with a concern for freedom from poverty among a sample of European countries. Secondly, they found that the inequality expansion from the early 1980s up until the beginning of the 1990s was largely due to the expansion of fair inequality in the United States. On the contrary, since the beginning of the 1990s, the majority share of inequality increase is considered to be unfair, driven by increasing violations of inequality of opportunities and freedom from poverty. Therefore, they argue that the inequality debate should focus more on the lower tail of the distribution.

The main point discussed in the following chapters is the idea that there could be unequally distributed opportunities among the population resulting from unequally distributed outcomes (Atkinson, 2015). These circumstances could lead to reduced formation of human capital through lower investment to the education. Reduced schooling would consequently enter the endogenous growth theory (Romer, 1986, Lucas, 1989) with potential endangered potential economic growth. We can find features of this hypothesis even in the work by Becker (1962). Becker claims that people do rational decisions about their investment to education via optimization between present costs and the sum of expected future returns. So that if under the present unequal circumstances an individual bears relatively higher costs with limited sources, the individual will more probably limit an amount of gained education in the lower tail of income distribution. This notion is described well in the theory of imperfect capital markets by Galor and Zeira (1993).

Regarding the inequality trends in recent decades, two questions use to be discussed repeatedly. First one asks why the within-country inequality has increased in the last decades so much among the developed world and the second one wonders whether increasing inequality is beneficial or instead prohibitive to economic growth. The literature is very complex in this field and results use to be ambiguous and depend strongly on the formulation of hypothesis, data availability, and methodology used. In the next section, we describe the actual situation and trends in inequality between and within countries. We also provide an analysis of theoretical concepts and consequent applied empirical research in this area.

The development process of between and within-country inequality was for a long time described by the famous Kuznets's theory. His theory implies that if we display the level of inequality as a function of development in gross domestic or national product per capita, the data traces out an inverted-U shape curve (Kuznets, 1955). The relevance of the Kuznets's theory was approved by the 19th- and 20th-century data. It describes well the development path during the era of industrialization in most of developed countries. The shortcoming of the basic Kuznets theory started in the second part of the 20th century. It seems to be valid only untill the 1970s when within inequality started to rise again in the most of world advanced economies (Piketty, 2014). This fact indicates that the theory about the basic Kuznets curve deserves more attention. Recent literature and empirical research based on the longitudinal sets of historical data describe the phenomena of inequality development as Kuznets cycles, rather than single Kuznets curve. The new cycle occurs with the emergence of a new technology revolution (Milanovic, 2016). It is the reason why Milanovic divides history to the preindustrial period with stagnating income per capita when the Kuznets cycles did not exist at all. Later, he names the industrial period with rising average income during the first and then second technological revolution described in the original Kuznets curve. During the technological revolutions not only GDP per capita increased, but also inequality did. The second part of the Kuznets curve captures the period between world wars and later, during the 1970s begins the next technical revolution based on the invention of semiconductors, computerization and resulting digitization of the economy.

The period, when the average income did rise and its inequality did as well, can be explained very naturally. Higher total income in the economy allows a certain part of the population to enjoy higher income without driving anybody else below an absolute starvation point. Higher total income simply gives more "space" for an increase in inequality assuming that everybody has at least the subsistence income. This process is well described by Milanovic et al. (2011) as the "inequality possibility frontier".

Milanovic further defines two types of forces (malign and benign) responsible for downward movements in inequality. Malign forces are characterized by idiosyncratic events such as occurs during wars (higher taxation for military purposes and reconstruction of after damage) civil conflicts (state breakdown), natural catastrophes, or epidemics. These events occur in societies with stagnant but also rising mean income. On the other hand, benign forces lead by social pressure through politics (socialism, trade unions), widespread access to education, ageing population (demand for increased social transfers, progressive taxation), and theoretical concept of technological progress that favours low-skilled workers. Benign forces are recognized only in societies with rising mean income (Milanovic, 2016).

It seems to be beyond the power of the simple Kuznets curve to explain upswing in inequality within rich countries after the 1970s. The consequent literature based on the skill-biased technological progress pioneered by Tinbergen (1975) advanced by Galor and Moav (2004) or later contributed also by Goldin and Katz (2009) reacted on the inequality rise in recent decades. The Race between Education and Technology together with theories about the accumulation of human capital offer one possible explanation for the increase of income inequalities within developed countries in the last decades. The following section is dedicated to the characterization of the phenomena of inequalities.

2.1 Inequalities of what and among whom

In the following paragraphs, we start the discussion about inequalities by description of its basic dimensions. In general, we could understand inequality as unequal distribution of any object among any population. Moreover, economic inequality has also different nuances and specific definitions occurs in the literature. Because every individual hypothesis is based on the narrow interpretation of inequality, specification of inequality is a key determinant for comparison between available empirical studies. In this section, we present the main forms of inequality important for further analysis. There are two main questions we need to ask about the inequality. It is important to know, the inequality of what do we measure, and who is the object among whom the inequality is measured.

Inequality among Whom? Atkinson (2015) summarizes the fact that there are many possibilities of how to measure even simple income inequality. Firstly, the researcher needs to define units of analysis. The main population units under consideration are mostly households, but inequality also use to be measured among different individuals. Definition and changing structure of households is constantly under discussion. Usually, the basic building unit, the family, has changed over the past thirty years. For instance, in many OECD countries the fertility rate has been persistently low with marriage rates down and high level of divorce rate, what lead to the trend of smaller, sole-parent or reconstituted families (OECD, 2011b) with increased assortative mating causing concentration of high-income couples (The Economist, 2017).

What is more, within the unit of a household, there may be distinct families, and within those families, we may distinguish different generations. As in the literature, the choice of a unit depends on the extent to which members of the household share equally its resources. Later, it depends also on the notion of control over these resources in the unit and on the degree of individual dependence. Ideally, all these should be taken under consideration, while deciding whether to count specific groups like grown-up children still living at home or elderly parents living with their children in the household unit. This issue is often neglected in public discussion (Atkinson, 2015) and may vary between scientific papers.

Inequality of What? The crucial point of any inequality analysis is to know the distribution of what we are concerned. On top of this, there are two main concepts for inequality in economics. Inequality of output and inequality of opportunities as two basic economic concepts. This differentiation is very important for our analysis in the following chapters. Both types of inequality are interrelated through the social mobility issue which is in the centre of discussion about economic development and poverty (WEF, 2020).

Later, the inequality of economic output concept continues into the discussion whether to focus on income, wealth, or consumption is the key indicator of true economic inequality. Standardly, the inequality is measured by the income of households. Because of the ambiguity of the right measure of inequality and its measurement method, we avoid estimation of inequality in this dissertation and use standard sources of inequality measure. We use a very standardized database with a harmonized Gini index of household income among world countries, based on historical national surveys. Regarding the measuring household income, Atkinson (2015) provides a very comprehensive schema of such a process with the aim of finding the total income of a household. To find the household income, we firstly add up earnings of every household member. Those earnings include not only the wages and salaries received by employees, but also the incomes of self-employed people, income from savings, which may take the form of interest (bank accounts or bonds), or maybe dividends on shares, or rent on property owned. So far, the sum of incomes represents the "Household market income". Later we add transfer payments received from private bodies, such as a pension, and state transfers from the government to get "Household gross income". Additionally, if we subtract income tax and other direct taxes, such as social security taxes, it gives "Disposable household income". After the raw household incomes are set, it is needed to account for differences in household size and its composition. The measure of family size is not taken on a per capita basis, but rather on the standardized economies of scale. Such a measure is called "Household equivalized disposable income". Finally, Atkinson provides the concept of "Household extended income", which we get if the value of public services, such as health, education, and social care can be taken under consideration (Atkinson, 2015).

The literature often discusses the important issue of national survey data representativeness on bottom and mainly on the top tail of the distribution. Benhabib et al. (2017) or Hlasny and Verme (2018), for all, find the biases on the measurement of inequality, especially for top earners. They also propose post-survey data adjustments, which are beyond the needs of this dissertation.

Less standard concept of measuring inequality is the distribution of consumption. This stream of inequality literature is based on criticism on income inequality which is poorly measured and does not accurately reflect true inequality. From all, we would mention the interesting finding of Meyer and Sullivan (2017), who use US consumption survey data for the last 50 years to emphasize differences between income and consumption inequality. They argue that US income inequality increased at a higher pace than its consumption equivalent and that income inequality rose in both halves of distribution while consumption inequality deepened only among rich.

Another concept of output inequality copes with wealth inequality which is usually higher than its income measure. We analyse the concept of wealth inequality in Section 2.4, where we compare it with income inequality on real data.

Finally, the last concept of inequality we would like to introduce is the inequality of opportunities. The theory based on the unequal distribution of opportunities focuses on the input side rather than the distribution of economic outcomes. This concept is important to provide a theoretical connection between the persistence of inequality between generations (Atkinson, 2015) and investments to human capital theories (Becker, 1962 or Galor and Zeira, 1993). This connection aims to be crucial to explain the interrelation between income inequality, human capital accumulation, and consequent economic progress. To the formalization of such models, we devote Section 2.3. The following section is dedicated to basic ways on how to measure and express inequalities by simple indicators.

2.2 Measuring inequalities

In practice, several inequality indicators can be found across the economic literature more frequently. It is striking that far the most popular measure of inequality is still the Gini coefficient by Corrado Gini (1912) It gains the popularity for its simple description of Lorenz curve (Max Lorenz, 1905) by a single number from an interval between 0 (perfect equality) and 1 (perfect inequality). 100 years later, our technology provides enormous data availability which offers much more composite measures, but once we want to cover historical data, Gini is the only option. On the other hand, we follow two trends in recent inequality measurement literature. The first one is an emergence of big datasets covering microdata on the national level represented by national censuses, surveys, or other government administrative data. Secondly, the recent advancement of technology allows to harmonize national microdata between countries. This data advancement stimulated the creation of the world income distribution presented in publications by Milanovic (2016) or Atkinson (2015). Their research based on the changes in the world income distribution represents an important and interesting source for economic analysis. It is interesting to follow winners and losers of the age of globalization and to find out the progress of which population parts of world nations are responsible for bridging the income gap between advanced and developing countries. This dissertation composes panel since 1970 and tries to cover a wide range of countries. Therefore, our analysis is based on a simple Gini coefficient which describes within-country disposable income inequality of households. Nevertheless, we would like to describe also other income distribution measures for deeper analysis in the next chapters.

For a better understanding of more complex dimensions of income distribution, we present several alternative indicators that could bring more light in additional analysis and discussion part of the dissertation. The reason we do not use these alternative indicators in our model is their seldom availability for even number of developed countries. As we already mentioned, inequality measures are in general aimed to describe the distribution of an object among the population. Present inequality measures are derived from national censuses datasets which are designed to reveal the distribution of income or wealth indicators on individual household level. In the following parts, we shortly introduce several usually available measurements of inequality and we directly apply real historical data from the United States and the United Kingdom to display recent inequality trends. Hence, the Gini index is used the most often, literature offers other several measures.

Firstly, quantile shares use to be often employed. For illustration, we provide some examples of quantile indicators applied in empirical studies. The income share of the fourth quintile on the whole population is for instance used in Persson and Tabellini (1994) while Alesina and Perotti (1996) analysed the impact of the income share of the third quintile on economic development. Another very popular indicator of inequality is the share of the top 1, 5, or 10 percent of the population. These measures are used mainly when speaking about the effect of top earners or about the concentration of especially wealth by a very narrow group of privileged people (Aghion et al., 2019). Later, a very comprehensive measure of inequality for only a part of income distribution is the ratio of quantile shares. Voitchovsky (2005) used 90 to 75 and 50 to 10 income shares to describe the upper and bottom tail of the distribution. More standard are quantile ratios in the proportion of 80 to 20 or 90 to 50 ratios (Atkinson, 2015).

Apart from the Gini index, literature provides some other index and coefficient measures like Theil index (Theil, 1967; Cowell, 2006), Atkinson index (Atkinson, 1970) or Robin Hood index (Kennedy et al., 1996) with their specifics. Later, Clarke (1995) used the advantage of the simple variation coefficient of income distribution for economic productivity analysis. Furthermore, the measure of the poverty rate needs to be mentioned as one of the most important inequality indicators. The poverty rate can be recognized as absolute poverty when speaking about the poor between countries and as relative poverty derived from the within-country distribution of income (Fosu, 2011; OECD, 2015).

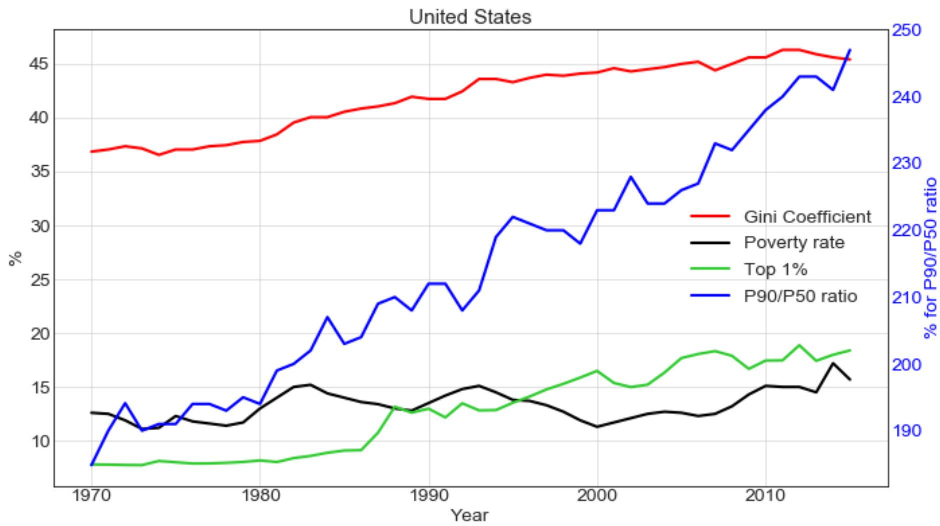
Relative poverty measures, as well as some other inequality variables, are exhibited in the following section to describe a complex picture of inequality to see behind the single measure of the Gini coefficient.

2.2.1 Measuring inequality on real data

The period between the 1970s and the present time can be characterized by the global increase of in-country inequalities. Atkinson (2015) presents the development of inequalities during this period in the United States (US) and the United Kingdom (UK) as countries with the most complete historical data sets. A recently constructed dataset by Atkinson et al. (2017) reveals an interesting insight into statistics of inequality, which provides more detail than a single measure of the Gini index. It allows us to see whether the increase in overall inequality was stimulated by the upper or lower part of the distribution. They harmonize time series for 25 world countries and control for other indicators that capture changes in the distribution of income. Some of these countries do not contain all indicators, but this dataset brings a new viewpoint on inequalities development in the last decades as we show in the next paragraphs.

In the following Figure 2.1 we present probably the best collected data for the United States. In the beginning, we see that the basic inequality measure of the Gini index describes the increasing trend in inequalities since 1970. Gini coefficient of overall income inequality increased from 37 to more than 45 in 2015. The next question naturally could be, which part of the income distribution did cause the change in The Gini index? The poverty rate which describes the share of population living in households with pre-tax cash income below the official poverty line has increased slightly. While more than 17 percent of US citizens lived below the poverty rate in 2014 these numbers oscillated around the level of 15 percent during the first years of the 1980s and the half of the 1990s. The right tail of the distribution is described by the share of the top 1 percent in gross income measure (tax units, excluding capital gains). It is obvious that the top 1 percent income share increased significantly. It increased during 45 years in the United States from almost 8 percent to more than 18 percent in 2015. We see disproportional gains from economic development even from these 2 indicators.

Figure 2.1 Inequality indicators for the United States (P90/P50 ratio on the second axis)

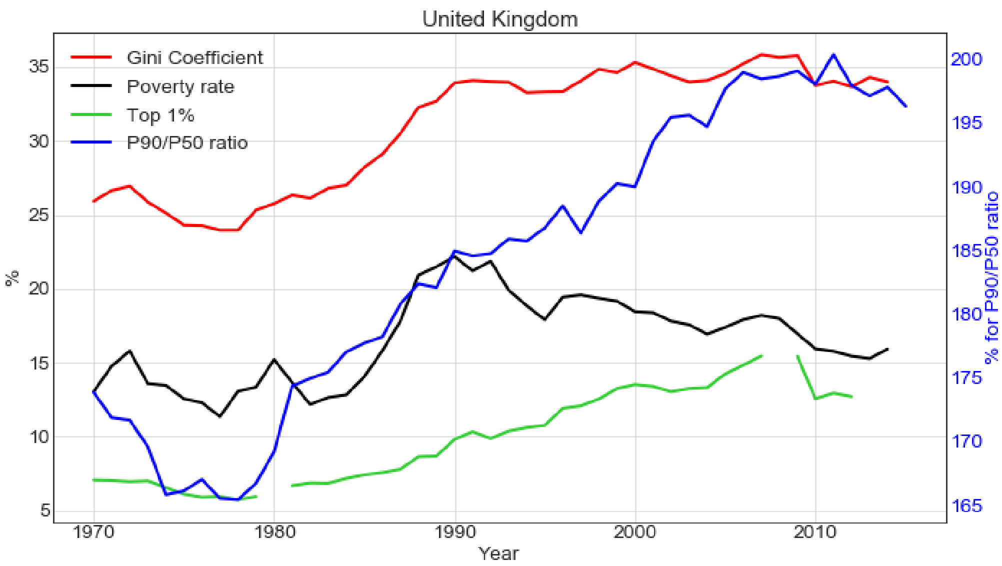


Source: Atkinson (2015) later Atkinson, Hasell, Morelli, and Roser (2017)

Later, the anatomy of distribution is captured well by the dispersion of earnings. The so-called dispersion of earnings is depicted as a blue line on the second axis. This ratio of earnings at the top decile and the median earnings increased significantly in the US during the recent 45 years. In 1970 the top decile earnings represented 185 percent of the median, but in 2015 the number increased to 247 percent. From the descriptive analysis of simple indicators, we see that the US inequality has increased in the recent 45 years in favour of the right tail of the distribution. In other words, the rich people represented by the upper decile or top 1 percent of the population, benefited the most from economic growth in recent decades, while keeping the poverty rate at relatively constant numbers (Atkinson et al., 2017).

The tendency of rising inequalities is slightly different in the case of the United Kingdom. While the Gini index increased from around 25 to more than 34 between 1970 and 2015, the major of this sharp rise happened just in nearly 10 years. The 10 points jump in the Gini index (from 24 to 34) can be observed between 1978 and 1991. After its strong growth, the Gini index oscillates around 34 points till 2015 in the UK. Comparing the Gini indexes between the UK and the US we see that the actual income inequalities are on the level of the US at the beginning of the 1970s. From the other inequality indicators, we see that the Gini sharp growth is followed by a significant increase in the share of population under the poverty line between 1982 and 1992. Poverty measure increased from more than 12 to 22 percent. Since the top in 1992 poverty rate decreased to the present value of almost 16 percent.

Figure 2.2 Inequality indicators for United Kingdom (P90/P50 ratio on the second axis)



Source: Atkinson (2015) later Atkinson, Hasell, Morelli, and Roser (2017)

On the right end of the income distribution, we see the UK inequality behaved similarly as in the US. We can note the increase in the share of the top 1 percent. The share of the top 1 percent in gross income was around 6 percent at the end of the 1980s and gradually culminated before 2008 at the level of 15,5 percent. After the financial crisis, this indicator declined by nearly 3 percentage points. Later, the earnings dispersion indicator, depicted on the right-hand axis, tells a similar story as in the US case. The ratio of earnings at the top decile and the median earnings increased between 1974 and 2015 by 30 percentage points. Its level was 165 percent in 1974 and culminated around 200 percent in 2011.

In the UK as well as in the case of the US, inequality favoured the upper tail of the distribution. Both countries experienced an increase in the income share of the top 1 percent and in the earning dispersion. The main difference between countries is their average level of inequalities, which is higher in the US. The second difference comes from the statistics about the poverty rate. While its level was during the whole period increasing only slightly in the US, the UK experienced its peak at the beginning of the 1990s and later downturn. Furthermore, in the case of the UK, there is a relatively stagnant Gini index since the beginning of the 1990s and stagnant earnings dispersion since 2005.

We introduced these additional inequality indicators to broaden the basic Gini coefficient analysis for later discussion of our results. Moreover, this section will be helpful in the following section dedicated to the actual literature about inequality of income, wealth and social mobility.

2.3 Inequality of income, wealth and social mobility

A very important topic not only for this dissertation is the theory about persistence of income inequalities among generations. Literature provides strong arguments that available resources during the individual's childhood significantly influence the level of her or his ability to adoption high skills. What later, in adulthood, determines an individual's income and consequently an overall inequality among generations. Atkinson connects the inequality of opportunity and outcome in social mobility issues. He claims that inequality of outcome directly affects equality of opportunity. Or in other words, that beneficiaries of inequality of outcome today transmit an unfair advantage to their children tomorrow (Atkinson, 2015). Concern about unequal opportunity, and limited social mobility, has intensified as the distributions of income and wealth have become more unequal. The broad literature was dedicated to the topic of social or economic mobility in recent decades (Corak (2006), Benabou and Ok (2001), Fernandez, Guner, and Knowles (2005))

The issue of social mobility (Lipset and Bendix, 1991) comes to the center of economic discussions because of the loss of potential talents in the form of human capital in unequal societies. Not only Kearney and Levine (2014) find that higher rates of income inequality might lead to lower rates of upward mobility through lower rates of human capital investment among low-income individuals. The World Economic Forum run yearly Global Social Mobility Index (WEF, 2020) for 82 countries with the top scoring European Nordic countries indicating the highest social mobility.

The concept of social mobility between generations can be understood in relative or in absolute terms. While the discussion in this regard is largely connected to the economic circumstances, it can be measured in reference to a wide range of outcomes, such as health or educational achievement in addition to income levels. Social mobility can also be understood as moving "upward" and "downward" while people's circumstances become better or worse off than those of their parents or within their lifetimes. World Economic Forum differentiates intragenerational mobility as the ability for an individual to move between socioeconomic classes within their lifetime and intergenerational mobility as the ability for a family group to move up or down the socio-economic ladder across the span of one or more generations. This concept is further extended on absolute and relative measures and education or income dimensions. Absolute income mobility is defined as the ability for an individual to earn, in real terms, as much as or more than their parents at the same age. Later, the relative mobility in education indicates how much of an individual’s educational attainment is determined by the education of their parents (WEF, 2020).

What is more the low level of social mobility leads to persistence in the accumulation of wealth among generations. This consequently leads to an additional increase in inequality of opportunity for the next generations. The effect of social mobility was recently examined by Benhabib et al. (2019) on the parsimonious macroeconomic model of the distribution of wealth in the United States. Unpleasant correlation between inequality of output and inequality of opportunities or income inequality and social mobility can be minimized by government interventions. Hassler et al. (2007) claim that public subsidies to education and educational quality produce cross-country patterns with a negative correlation between inequality and mobility and for that reason it diminishes the negative effect of intergenerational persistence of inequality. OECD (2011a) later finds that the relationship between parental or socio-economic background and offspring educational together with wage outcomes is positive and significant in practically all OECD countries for which evidence is available. They recommend to support higher enrolment in childcare and early childhood education, because it correlates with a lower influence of parental socio-economic background on a teenagers' cognitive skills. These policies are likely to be most efficient when they are targeted to children from low-income or second-language families.

Castello (2010) summarizes that the most important influence on social mobility has access to education. The second determinant of economic mobility is the nature of a country's institutions and government. And the third determinant of economic mobility is the nature of marriages in a country also known as assortative mating. Already Becker and Tomes (1986) emphasized on the importance of educational policies on intergenerational transmission of human capital and the importance of family backgrounds in affecting human capital investment. This notion gradually continues to the theory about the accumulation of human capital, which describes the choice of whether to invest in human capital. The decision about years dedicated to education is based not only on available resources, but it takes into consideration also the sum of life incomes from the additional year of schooling (Becker, 1962). We describe this stream of literature in Section 4.3.

In this part, we wanted to underline the importance of distinguishing between inequality of opportunity and inequality of outcome regarding the economic mobility effect on the accumulation of productive factor of human capital. Equality of opportunity would be achieved when circumstances out of individuals control do not play any role in the resulting outcome. Using Atkinson's words, inequality of opportunity is essentially an ex-ante concept, meaning that everyone should have an equal starting point. It is the existence of a highly unequal distribution of prizes (outcomes) that leads us to attach so much weight to ensuring that the “race” is a fair one (Atkinson, 2015).

2.4 Current Discussion on Inequalities

The recent World Economic Forum (WEF, 2020) emphasized increasing inequality as one of the main issues of the present world. Positively, trends from the last decades show that countries become more equal in the meaning of income per capita, so that between countries inequality decreases. On the other hand, increasing inequality within countries might cause serious economic consequences. International forum sees in increasing inequality a potential source of "risk of social unrest", "risk of populism" and "migration" to the future. Later, they point on decreased social mobility which undermines the economic potential of countries. To support equality of opportunities for youth from different social backgrounds is a policy recommendation how to fight mainly within-country increasing inequalities.

2.4.1 World wealth inequalities

The overall world inequality is illustrated well on the inequality of wealth between developing world regions and super-rich individuals. While inequalities between countries are decreasing, actual inequality is enormous, what brings heterogeneity to other models. Attractive estimations of world wealth inequalities have been presented by several institutions in recent years (Oxfam, Credit Suisse, World Bank). On the other hand, the income inequality comparison for a long-time span is a challenge from methodological point of view. Even if it is difficult to harmonize purchasing power parity between countries and to control for constant prices at the same time some, databases managed to assemble the World Income Inequality Database (Solt, 2016). In this section, we present finding about between countries inequalities.

Oxfam considers the present trend in economic inequality to be out of control. Their main message from the last WEF is supported by many inequality statistics. Oxfam compares income and wealth distribution data among the world regions and provides arguments about deepening wealth inequality between the richest and the poorest which may have alarming impacts on the future. They claim that in 2019, the world's richest 1% have more than twice as much wealth as 6.9 billion people. Later, they estimate that the world's billionaires, only 2,153 people, had more wealth than 4.6 billion people in 2019 and only 22 richest men in the world own more wealth than all the women in Africa. These facts underline the existence of extreme wealth concentration and at the same time the great world poverty (OXFAM, 2020). The Credit Suisse wealth monitoring of world wealth distribution provides alarming statistics, when the bottom half of wealth holders collectively accounted for only less than 1% of total global wealth in 2019. While the richest 10% own 82% of global wealth and the top 1% alone own 45% (Credit Suisse, 2019). The great gap in the present world wealth distribution is also documented in the new World Bank estimates (Lange et al., 2018), which show that almost half of the world's population lives on less than $5.50 a day, and the rate of poverty reduction has halved since 2013 (OXFAM, 2020). As would be expected wealth inequality is lower within individual countries. Typical average values for individual country wealth distribution would be 35% for the share of the top 1% and 65% for the share of the top 10%. But these levels are still much higher than the corresponding figures for income inequality, or any other broad-based welfare indicator (Credit Suisse, 2019).

The regional pattern of wealth distribution can be explored further by assigning adults to their corresponding global wealth positions as do Milanovic (2010) with comparable incomes of households. Credit Suisse calculations indicate, for example, that a person needs net assets of USD 7,087 to be among the wealthiest half of the world citizens (in 2019). However, 109,430 USD is required to be a member of the top 10% of the global wealth holders, and 936,430 USD to belong to the top 1% (Credit Suisse, 2019).

2.4.2 Advanced countries and inequalities

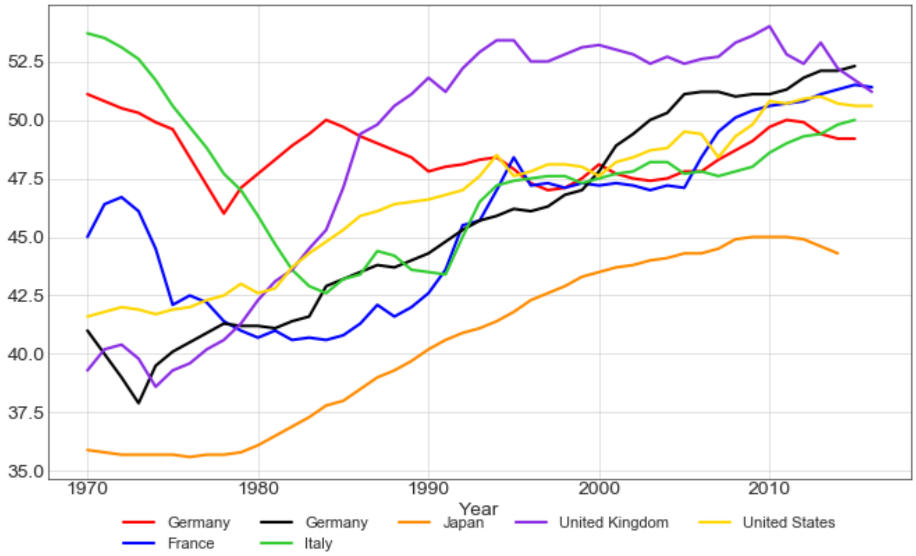
Inequality trends in the advanced part of the world are well documented by OECD reports. In the following section, we mostly summarize recent findings about increasing income inequalities and the distribution of wealth within advanced countries.

In the most advanced countries, the gap between rich and poor is at its highest level for the last 30 years. Income inequality increased in OECD countries in good times as well as in bad times. Today, the richest 10 percent of the population in the OECD area earn 9.5 times the income of the poorest 10 percent while in the 1980s this ratio stood at 7:1 and has been rising continuously. Incomes at the bottom grew much slower during the prosperous years and fell during downturns (Cingano, 2014). Other measures of inequality also support the general picture of increasing inequality. The Gini coefficient of income inequality stood at 0.29, on average, across OECD countries in the mid-1980s. But by 2013, it had increased by about ten percent or 3 points to 0.32. Inequality increased in 17 of the 22 OECD countries for which long-time series are available. In emerging economies levels of inequality are generally higher than in OECD countries (0.5 in Brazil and many other Latin American countries, with the highest 0.7 inequality in South Africa) (OECD, 2015).

People with skills in high demand sectors like IT or finance have seen their earnings rise significantly faster, especially at the very top end of the scale, where performance-based pay and bonuses have become widespread. Meanwhile, at the other end of the distribution, wages of workers with low skills have not kept up this pace. In three-quarters of OECD countries, household incomes of the top 10% grew faster than those of the poorest 10% in the two decades prior to the global economic crisis (OECD, 2015).

We shortly describe increasing income inequality among the world's most developed countries over the last decades in the following figures. Disposable household income inequality measured by the Gini index demonstrates increasing within-country inequality since the 1970s or 1980s in some countries. Figure 2.3 is dedicated to a sample of the most developed countries since the 1970s. We see that probably except Germany, all of these countries have experienced a continuous increase in income inequalities since 1970 or 1980.

Figure 2.3 The Gini index of disposable household income among a sample of OECD countries

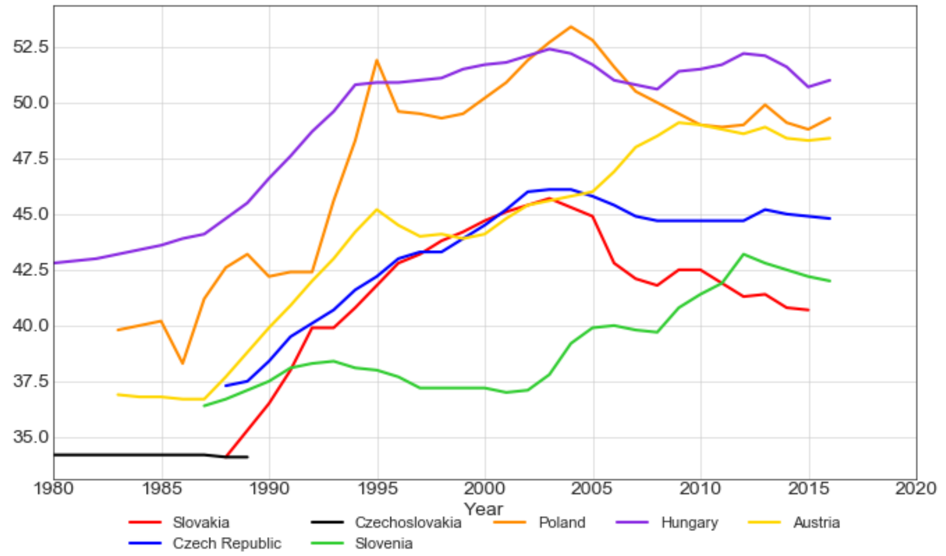


(Source: SWIID database)

You probably recall that levels of inequality are different than those from the previous chapter. The reason is a different source of data. While in the previous section we use the original data from Atkinson's (2015) database, we use the advantage of the Standardized World Income Inequality Database by Solt (2009) in the following figures.

Later we focused our attention on Slovakia and its neighbouring countries. Figure 2.4 depicts data from mostly former communist countries (Slovakia, Czech Republic, Poland, Hungary, and Slovenia), so the increase in inequality after 1989 is expected. But we see that the same increase can be observed also in the case of democratic Austria. Unfortunately, data for small countries and those with communist history are limited, that is why they are not present in all outcomes of our later empirical analysis.

Figure 2.4 The Gini index of disposable household income among V4, Austria and Slovenia



(Source: SWIID database)

Later, we summarize wealth inequality among the developed world. Naturally, wealth inequality is among OECD countries distributed more unequal than income. The picture about wealth inequalities among advanced economies can be described through the household wealth distribution from the second wave of the OECD (2020) Wealth Distribution Database. Firstly, they estimate that wealth concentration is twice the level of income inequality across the 28 OECD countries covered. The wealthiest 10% of households hold, on average, 52% of total household wealth, while 60% of poorest households own slightly over 12%. What is more, up to a quarter of all households report negative net worth in several countries. Besides, some countries indicate large shares of households with high levels of debt relative to both their incomes and the assets they hold. More than one in three people are economically vulnerable, as they lack liquid financial assets to maintain a poverty-level living standard for at least three months Balestra and Tonkin (2018). These findings are crucial determinants for children opportunities in such households. That is why the concern about equal opportunities regarding the accumulation of human capital is on the place.

3 Theory of economic growth

Since the neoclassical models of Solow (1956), Cass (1965) and Koopmans (1965), modern economy has focused interest on determinants of economic growth or on an explanation which factors determine economic productivity differences between world nations. In the previous chapter, we described the differences in average gross domestic product per capita as a kind of world inequality or inequality between countries. The objective of growth theories is to explain this kind of inequality between economies. Solow (1956) defines the standard neoclassical production function with decreasing returns to capital. He defines a growth model where inputs of labour and capital stock determine economic output in the form of GDP. Production function with exogenously given rates of saving and population growth determines the steady-state level of income per capita and so the inequality between countries. Technological change was for decades modelled as an exogenous factor. Technological revolutions were treated as a matter of coincidence or luckily occurrence of scientific inventions.

Later, the endogenous theories by Lucas (1988) or Romer (1990) encouraged a new stream of theories based on an idea, that the technical progress can be assigned to human creativity, education, and scientific research. After the formulation of the first endogenous models, the identifying economic growth key determinants has flourished. The period of the 1990s started with the extension of the basic Solow model by Mankiw, Romer and Weil (1992). They took the basic Solow model seriously and used the already available datasets to estimate his assumptions on real data. They found that the model is valid but there is missing important factor of productivity in the form of human capital.

Empirical findings of Mankiw, Romer and Weil (1992) together with the formulation of endogenous growth theories had been only the first step to the modern growth theories published in the consequent decades of the 21st century. The following section shortly describes the basic growth theories and presents also some findings from the modern growth approaches based on the recently collected datasets (Lutz et al., 2008, Goldin and Katz, 2009, Acemoglu and Restrepo, 2018, Flabbi and Gatti (2018) and many others).

3.1 Basic growth theories and introduction of human capital

As we already mentioned Robert Solow (1956) in his classic article proposed the model of economic growth by assuming a standard neoclassical production function with decreasing returns to capital. He took the rates of saving and population growth as exogenous. He showed that these two variables determine the steady-state level of income per capita and so the inequalities between countries. Because saving and population growth rates vary across countries, different countries reach different steady states. Later research confirmed that predictions of the Solow model are, to a first approximation, consistent with available empirical data (Mankiw et al., 1992). Weil in his textbook (2013) starts the explanation of economic growth with the Solow model as basic Cobb-Douglas production function (3.1) with properties of constant returns to scale and diminishing marginal product where A is exogenously given technology, K represents capital stock and L labour or population size:

$$Y = F(K, L) = AK^{\alpha}L^{1-\alpha} \tag{3.1}$$

Later Mankiw, Romer and Weil (1992) reveals that the original Solow model based on the population growth and the accumulation of physical capital does explain differences among countries productivity better with including the quality measure of labour in the form of the accumulation of human capital measured or approximated by the stock of education (H). They show on empirical data that such a definition of the model (3.2) provides an excellent description of the cross-country differences. The evidence indicates that, holding population growth and capital accumulation constant, countries converge at about the rate the augmented Solow model predicts. Mankiw, Romer and Weil describe the production as follows:

$$Y_t = K_t^{\alpha}H_t^{\beta}(A_tL_t)^{1-\alpha-\beta} \tag{3.2}$$

and provide also the first estimations of elasticities for the basic production factors namely capital stock (K), human capital stock (H) and labour or population (L):

$$Y = K^{1/3}H^{1/3}L^{1/3} \tag{3.3}$$

Their findings were under the discussion during the 1990s when the broad literature covering growth models focusing on the importance of human capital, namely on education, was in the centre of economic research. From all, we would mention contribution of only a few of them. Benhabib and Spiegel (1994) reveal that schooling years display a positive association with economic growth. Moreover, Lee and Lee (1995) report a significantly positive influence of secondary school test scores on economic growth. Later, Hanushek and Kimko (2000) show that labour force quality measured by mathematics and science test scores is growth-enhancing and a big number of other studies with a positive impact of schooling on productivity differences between countries. On the other hand, studies like Bils and Klenow (2000) were more sceptic about the findings based on Mankiw, Romer and Weil (1992) estimates. They argue that the channel from schooling to growth is too weak to plausibly explain more than one-third of the observed relation between schooling and growth. They refer to the endogenous aspect of education. They claim that the cross-country schooling–growth association does not primarily reflect the growth effect of schooling but may partially be due to the impact of growth on schooling (Bils and Klenow, 2000).

After the construction of the first panel datasets, the picture about the essential role of human capital in growth models became undeniable. For instance, using the panel structured datasets, Barro (2001) confirms the positive schooling–growth nexus. De la Fuente and Domenéch (2006) find that there is a systematic relationship between data quality and the size of OLS estimated coefficient of human capital. They later provide evidence on improved human capital dataset of 21 OECD countries to deliver findings that if educational variables turn out to be insignificant or to have the "wrong" sign in growth regressions, it can be attributed to deficiencies in the data and that improvements in data quality lead to larger and more precise estimates of schooling coefficients in growth regressions. Moreover, the significance of the schooling in growth regression using more sophisticated measures is provided by Cohen and Soto (2007). They attempt to account for population structure while constructing education variables and to cope with the issue of endogeneity. Their augmented Solow production function that embeds the Mincerian approach to human capital delivers a piece of evidence that the improved series of human capital are highly significant in growth regression.

In this view, the work of Benos and Zotou (2014) is interesting. Their literature review and meta-analysis of results covering more than 2 decades of papers focusing on the relevance of empirical macroeconomic estimations about the relationship between education and economic growth delivers an interesting overview. Analysis of 57 empirical studies and 989 estimations concludes that although there is substantial publication selection bias toward a positive impact of education on growth, but once they account for this, the genuine growth effect of education is not homogeneous across studies but varies in positive numbers according to several factors. Specifically, it is attributed to differences in educational measurement and study characteristics. Mainly model specification as well as the type of data used, and the quality of research outlets where studies are published (Benos and Zotou, 2014). While the magnitude of the human capital effect on economic growth and productivity is uncertain and its marginal effect after incorporation of other factors is discussed, the final effect of human capital on economic growth is according to broad literature definitely positive. As Flabbi and Gatti (2018) summarizes: “Both theory and evidence show that investing in human capital is a promising strategy to attain stable positive growth. But the magnitude of the effects remains country-specific, varying based on the population of interest, the policy under consideration, and the human capital component considered”.

Later, Flabbi and Gatti (2018) describe well two-fold relation from human capital to potential economic growth by distinguishing its direct and indirect effects. Firstly, the direct effect implied by its accumulation of human capital analogous to physical capital accumulation as in Lucas (1988):

$$Y = AF(K, vH) \tag{3.4}$$

v denotes current stock of human capital devoted to production and the $(1 - v)$ in (3.5) represents the proportion devoted to further skill acquisition. There is the trade-off of whether to invest present stock of human capital into further knowledge or skill acquisition with an opportunity cost of not using it in production. The second part of relation is the indirect impact of human capital on technology progress:

$$A = G[(1 - v)H] \tag{3.5}$$

human capital is an input that can be used to produce new knowledge A, which then increases Y through additional gain of skills (Flabbi and Gatti, 2018).

Research in recent decade was built on high-quality datasets covering a wide range of countries. These datasets together with advanced models incorporate assumptions from endogenous-growth theory presented in the next chapter. Endogenous growth models have developed since Lucas (1988) and Romer (1990). Present models assume more complexity of interrelations and view the technological progress as a process whereby purposeful research and application lead over time to new and better products and methods of production and also to the adoption of superior technologies that were developed in other countries or sectors (Barro, 2013). Identifying the true effect of various definitions of human capital and the search for causality continue in the process of estimating more detailed and more accurate data. The relatively new stream of human capital theories is based on the skill-biased technological progress. This evolving stream of literature emphasizes the importance of education quality of certain skills or knowledge for the invention of new technologies and its following adoption by mass population with consequences on the distribution of income and output (Goldin and Katz, 2009; Acemoglu et al. 2011, Acemoglu and Restrepo, 2018).

Recently, Flabbi and Gatti (2018) claim that "*human capital investments produce returns only if they generate valuable skills*". Interesting stream of economic models based on the labour specific skills is beyond the scope of this dissertation. At the end of this chapter, we summarize the direct impact of human capital on economic output through increased productivity of the labour activated in production. Moreover, we count for indirect impact through influence of education and research on technological progress, which able to increase the productivity of all the production factors. The interaction between physical and human capital, affects the returns of a given mix of the two main production factors through skill-biased technology (Flabbi and Gatti, 2018).

3.2 The accumulation of human capital

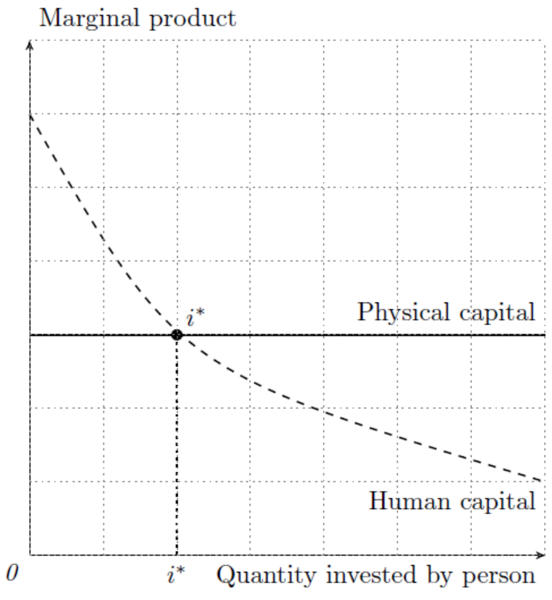
As we already described, human capital is widely regarded as a fundamental input in the theoretical growth literature (Botev et al., 2019). The fruitful stream of literature dedicated to the phenomena of human capital begins with the contributions of Schultz (1961) and Becker (1962), who focused their research on the variability in productivity between workers based on their qualities. They define human capital more broadly as the set of knowledge, skills, competencies, and abilities embodied in individuals and acquired, for example, through education, training, medical care, and migration.

Later, by the words of Barro (2013), the general label of human capital represents a common pool of labour skills and personal qualities that make an individual more productive and consequently to earn a higher wage. Although human capital includes education, health, and aspects of "social capital.

While a wider definition of human capital includes health, the human capital is more often simplified on education and alternatively defined as the stock of knowledge, skills, and other personal characteristics embodied in people that help them to be more productive. Investment in human capital includes investment in formal education (early childhood, formal school system, adult training programs), but also informal and on-the-job learning and work experience (Botev et al., 2019).

The definition is captured well also by Weil (2013), who describes characteristics of human capital through the comprehensive comparison between physical and human capital features. Human and physical capital are both productive (it enables them to produce more output), both of them represent qualities that are produced (it is a result of previous investment) and human capital, as well as physical capital, earns a return and also depreciate. On the contrary, the important characteristics which differentiate these two are that human capital is embodied in an individual. Human capital earns a return by giving the worker who owns it a higher wage, and only does so while he or she is working, whereas physical capital can earn its return while its owner is passive (Weil, 2013). This certain feature of human capital plays the main role in explaining returns to investment into human versus physical capital and it is a key point for the accumulation of human capital through individual decision making about future education under the assumption of inequality of sources and imperfect markets (explained in Section 4.3).

Figure 3.1 Decreasing marginal product of investment to human capital



Source: Weil (2013)

The individual decision making about years of education is explained in the Figure 3. 1. Because the marginal product of human capital declines with the quantity that an individual invests, the line representing the marginal product of human capital is downward sloping. If a person has less than i^* available to invest, he or she will invest all resources in human capital. If he or she has more than i^* to invest, then he or she will invest i^* in human capital and the rest of his or her money in physical capital (Castello and Domenech, 2002). That is why rich individuals, could invest i^* in education and the rest to physical capital. But the poorest are limited to invest even i^*, so that their potential knowledge or skills are biased by their current sources and economy loses potential productive factor.

Literature about the human capital accumulation lists several education measures as human capital proxy. The quality of these human capital estimations has developed significantly in recent years. Basic education proxies from the 1990s had solely the quantitative form of basic enrolment rates (Mankiw et al., 1992), mean years of schooling (Barro and Lee, 1993; Bils and Klenow, 2000) or investment to education. Later, since the contribution of Hall and Jones (1999), literature accounts for the dimension of returns to an additional year of schooling. Following the original theory of Mincer (1975), Hall and Jones estimate returns to an additional year of schooling on the aggregated global level and apply for years of schooling in each individual country.

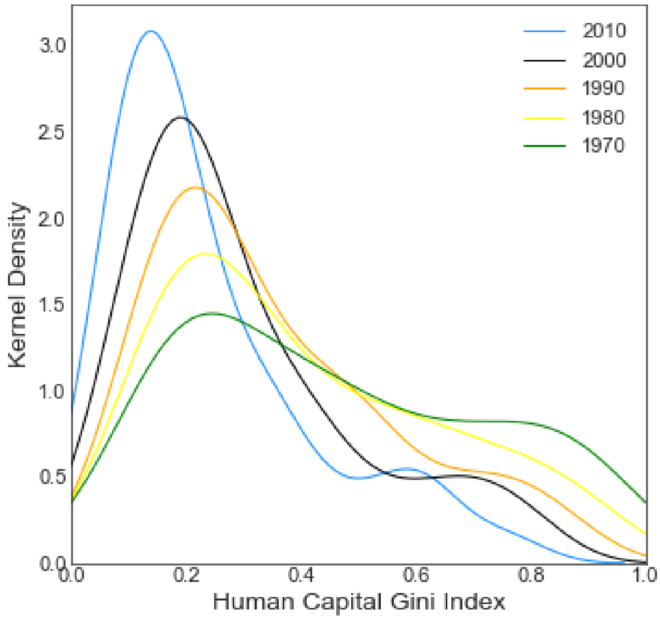
The work of Hall and Jones (1999) was improved by recent OECD report. The OECD team introduces novel Mincerian coefficients based on the realistic rates of return to education consistent with the private returns to education, which are allow variations among countries and to some extent over time. The new measures perform well in regression analysis explaining productivity across OECD countries and over time better than studies with equivalent measures (Botev et al., 2019).

Later, there is a significant literature focusing on the estimation of the quality aspect of accumulated human capital. Results from test scores such as the OECD's PISA or PIAAC seem to be a more robust driver of economic growth than usual education quantity proxies (Hanushek and Woessmann, 2012; Barro, 2013; Barro and Lee, 2015). On top of these, Altinok et al. (2018) provides Global data set for 163 countries on education quality for the period of 1965-2015 based on the International Standardized Achievement Tests[1] (ISATs). The paper concludes that the quality of the educational system matters. Its results validate the positive and significant association between educational achievement and economic growth. Also, the paper finds that the learning outcomes in developing countries cluster at

[1] ISATs is the harmonized evaluation of education in different regions of the world by International Association for the Evaluation of Educational Achievement which is an international cooperative of national research institutions, governmental research agencies, scholars, and analysts working to research, understand, and improve education worldwide.

the bottom of a global level and that while the variation in performance is high in developing countries, their top performers still often perform worse than the bottom performers in developed countries (Altinok et al., 2018).

Figure 3.2 Kernel densities for human capital inequalities between 1970 and 2010



Source: Author's calculations based on Castello and Domenéch (2002)

The third special extension of the general measure of human capital is provided in Castello and Domenéch (2002). They introduce analysis based on the variable of human capital inequality[2] as we present on Figure 3.2. Human capital inequality provides more robust estimations in growth models than income inequality measures. Using cross-country data on human capital inequality they conclude that most countries in the world have tended to reduce the inequality in human capital distribution (Castello and Domenéch, 2002).

[2] The human capital Gini coefficient (G_h) can be computed as follows:

$$G_h = \frac{1}{2\overline{H}} \sum_{i=0}^{3} \sum_{j=0}^{3} |\hat{x}_i - \hat{x}_j| n_i n_j$$

$$\hat{x}_0 \equiv x_0 = 0,\ \hat{x}_1 \equiv x_1, \hat{x}_2 \equiv x_1 + x_2, \hat{x}_3 \equiv x_1 + x_2 + x_3$$

where $\overline{H}$ is the average schooling years of the population aged 15 years and over, i and j stand for the different levels of education, n_i and n_j are the shares population with a given level of education, and $\hat{x}_i$ and $\hat{x}_j$ are the cumulative average schooling years of each educational level.

The fourth extension of human capital measures represents the database by the International Institute for Applied Systems Analysis (IIASA) and the Vienna Institute of Demography (VID). Their dataset is based on the demographic method of multistate back-projection. They compile a full reconstruction of educational attainment distributions by age and sex for 120 countries back to 1970 with the following predictions projected to the 21st century (Lutz, Goujon, KC, Stonawski, and Stilianakis, 2018[3]). The research of Cuaresma et al. (2013) took the advantage of this unique panel data to show not only that the improvements in educational attainment are the key to explaining productivity and income growth, but also that a substantial portion of the demographic dividend can be assigned to education dividend. The paper from 2013 is a reaction to their previous contribution in 2008. Lutz et al. (2008) introduce the unique dataset from above and explain the importance of demographic aspects in the discussion about the improvement in education statistics. Their results show consistently positive, statistically significant education effects on economic growth for individual age and education groups. Later, they propose development scenarios differentiating the contribution of individual level of education on economic growth.

The inspiration for our analysis comes from the paper of Lutz et al. (2008). They introduce human capital to the production function as a labour force input and through the absorption rate of new technologies, which, in turn, depends on the interaction between human capital and distance to the technological frontier. The distance from the technological frontier is measured according to the level of productivity. It is the "distance" in GDP per capita from the top-performing country. Their contribution in comparison to previous literature is in the composition of human capital. They differentiate the share of population in each education level and 5-year age cohort matrix and interact them with the distance from the technological frontier. Doing so, they find clear two-fold importance of human capital accumulation without the effect of changing age structure (Lutz et al., 2008).

This dissertation thesis aims to contribute by implementation of the nonparametric approach advantageous feature. Its advantage is the identification of the convex envelope of an efficient or technological frontier instead of using GDP per capita as a priori determinant of technological advancement. We explain the differences between deterministic and stochastic or between parametric and non-parametric methods later in Chapter 5.

[3] Database is easily accessible on the web page of Wittgenstein Centre http://dataexplorer.wittgensteincentre.org/wcde-v2/

4 Inequality and economic growth

Discussion about the relationship between inequality end economic growth use to be twofold and influenced by the reverse causality. Literature provides arguments for the impact of economic development on the level of inequalities as well as the effect of inequality on economic progress. In both cases, the direction of impact is often ambiguous across papers and different theoretical approaches. In this section, we introduce a literature review for both theoretical streams. The first part is dedicated to the effect of economic growth and technology progress on inequalities and the second part describes the effect of inequalities on economic growth, which is more important for our analysis. Finally, we explain in more detail the theory about the human capital accumulation under the imperfect capital market assumption, which is important for formulation of our nonparametric model in Chapter 5.

4.1 Effect of economic growth and technology progress on inequalities

Since the famous Kuznets theory (1955), there is a strong effort to find a systematic relation between economic development and the level of inequality. The evidence from the 19^{th} and most of the 20^{th} century validates notions of Kuznets theory. The Kuznets theory seems to be valid until the 1970s what stimulated new concepts. The story of the 20^{th} century is described well by the long-run model of Galor and Moav (2004), who formulate theory capturing the endogenous replacement of physical capital accumulation by human capital accumulation as a prime engine of economic growth in the transition from the industrial revolution to post-industrial growth. Their model explains the role of inequality in this transition during the 20^{th} century. In the following paragraphs, we introduce assumptions and findings of their model and describe recent theories.

Model formulated by Galor and Moav (2004) is based on three central elements supported by available evidence: 1) the marginal propensity to save and to bequeath increases with wealth inequality so that inequality has a positive effect on aggregate savings, 2) mechanism of the credit market imperfection says that credit constraints undermine investment in human capital and 3) the economy is characterized by capital–skill complementarity. The accumulation of physical capital increases the demand for human capital and induces human capital accumulation.

In the early stages of industrialization, physical capital is scarce, the rate of return to human capital is lower than the rate of return to physical capital and the process of development is fuelled by capital accumulation. The positive effect of inequality on aggregate saving dominates, the negative effect on investment in human capital is minor, what leads to rising inequality and increasing aggregate savings. Aggregate saving are enables physical capital accumulation what enhances the process of development (Galor and Moav, 2004). As the physical capital accumulates, complementarity between capital and skills gradually increases the rate of return to human capital and stimulates investments to human capital.

In later modern development phase human capital emerges as a growth engine, equality alleviated adverse effects of credit constraints on human capital accumulation, stimulating the growth process. The negative effect of inequality on investments to human capital dominates, what encourages counter inequality policies. There are two interconnected approaches that explain processes during this phase. The first one is the model of imperfect capital markets (Galor and Zeira, 1993) better explained in Section 4.3. And the second one is based on the skill-biased technological progress (Goldin and Katz, 2009).

In skill-biased technological revolutions learning investments required by new machines are greater than those required by pre-existing machines. Skill-biased revolution triggers reallocations of capital from slow- to fast- learning workers, thereby reducing the relative and absolute wages of employees from old industries (Caselli, 1999). This period is characterized by Galor and Moav (2000) as an increase in the rate of technological progress which raises the return to ability and simultaneously generates a rise in wage inequality between and within groups of low- and high- skilled workers. That is why, the advanced countries have experienced rapid technological progress along with fundamental changes in the pattern of wage inequality in the last decades. Galor and Moav (2000) further expect, that as the economy would converge to the steady-state the rise in the rate of technological progress would diminish. Due to the feedback from growth to capital markets, it would increase the supply of skilled workers and temporarily decrease wage inequality between high-skilled and low-skilled labour with a possible cyclical process in the wage differential between high-skilled and low-skilled labour.

The increase of income inequalities within developed countries in the last decades is captured well in the work of Goldin and Katz (2009). The name of their publication "The race between technology and education" is more than accurate. It shares common assumptions and results with the previous work of Galor and Moav (2000). They explain the enormous rise of inequalities in the US since the 1970s through skill-biased technology which increases the return to education. They find semiconductor and computer technology requiring new skills and higher educated employees responsible for the rapid growth of college wage premium in general or as Caselli (1999) suggested a premium for scarce skills needed in novel industries. Such a wage premium deepened the gap between white- and blue-collar labour in the last decades of the 20th century. So that returns to education copy the U-shaped curve during the 20th century according to the relative demand for skills and their available supply. The decreasing trend in the first part is caused by publicly available education and they explain an increasing trend in the second part by the skill demanding technology progress. Goldin and Katz capture the story of the 20th century and the rise of semiconductor technology and computerization. But the 21st century brings even more advanced technologies, which could have a serious impact on labour market and inequality in following decades.

The latest research focuses more on digitalization and robotization with the potential to influence labour markets in unprecedented magnitude through the risk of automatization. Acemoglu and Restrepo (2018) continue with many ideas from Goldin and Katz and publish a paper called "The Race between Man and Machine". Title of this paper describes well broad stream of literature about predictions on automatization of certain jobs by machines with potential consequences on the distribution of income and wealth in the future. But this interesting topic is beyond this dissertation thesis.

4.2 Effect of inequalities on economic growth

Over the last decades, it has been discussed extensively how inequality may affect economic growth. Theoretical and empirical scientific research came up with several theories and arguments that economic growth is undermined by unequal distribution of income or wealth as well as notions that inequality is instead good for growth in certain cases. The methodological approaches, the data quality, availability, and granularity has developed significantly in recent years. The robust results from the recent research converge to the outcome that equal distribution of income, wealth, and opportunities leads to more sustainable economic growth (Berg and Ostry, 2018). As the main channel behind this mechanism is considered the theory that human capital accumulation is affected by unequal distribution of sources under the assumption of imperfect capital markets. Inequality is an important determinant for investments in education. It influences decision about quantity and quality of human capital stock (OECD, 2015).

Nevertheless, the results of a large proportion of inequality research on how inequality may affect economic growth has not provided a conclusive answer. For better understanding the present state of the art, we would go through existing literature to show different aspects of this issue. Later, the conclusion from empirical research seems to depend notably on the econometric method employed, and the data considered (Voitchovsky, 2005). For the critique by Voitchovsky, literature review requires further analysis on the first sight contradictory results. Because each study published so far is based on the different data samples with ambiguous quality, various time range, the sample of countries, questionable inequality indicator, and analysis method used, we need to consider all the details for interpretation of empirical result.

Recent research looks reliable because the quality and granularity of inequality data have increased significantly, and available samples have widened over the last decades. Consequently, available models have got enriched by new possible channels through which economic growth may be affected by unequal distribution and a big portion of theoretical hypotheses have been verified by numerous empirical works. An actual rich system of literature explaining the relationship between inequality and economic growth is drafted well in previous works by Vitchovsky (2005) or OECD (2015). The logical classification of diverse theoretical and empirical approaches is needed for clarification of partial results. Naturally, the first stage criteria in this classification mirrors whether the article concludes the positive or negative influence of inequality on economic growth. Later, OECD structures the literature according to the channel through which inequality may have an impact on the growth. They recognize 3 channels of negative impact, namely "the theory of endogenous fiscal policy", "the theory of imperfect credit markets" and "the theory of minimum critical amount of domestic demand". Moreover, there can be found theories with positive relation divided into two groups following "the hypothesis of inequality as an incentive to work harder" and "the theory of higher inequality fostering investments through capital accumulation of rich". Different categorization of literature is used in Voitchovsky (2005). She instead focuses on the historical patterns of economic research. The literature from the last decades is sorted according to periods in which different types of data were available. Various methods might consequently determine their empirical results. For all, Vitchovsky provides an example of works by Partridge (1997) with positive relation from cross-section data and Panizza (2002), who uses panel data techniques and reports a negative impact of inequality on growth.

Last, but not least aspect we need to have in mind during the literature analysis is the measure of inequality. Recent studies among the world countries provide very advanced and detailed distribution statistics rather than a single measure of inequality (mostly the Gini index). Harmonized national surveys and government register data are holy grail sources to study inequalities on the individual level. Important is also, that these datasets focus on income before and after redistribution as well as on wealth statistics in advanced countries in recent years. On the other hand, the availability of comparable historical data is challenging. There are only a few databases, which harmonize inequality data and provide a long enough time span with a sufficiently wide range of countries for panel data. A comparison of results is also linked to a discussion about reverse causality between income inequality and economic growth. Several studies have also looked at the reverse causality on the effect of economic growth on specific parts of the population among the wealth or income distribution (Dollar and Kraay, 2002, Voitchovsky, 2005 or Foelmi and Zweimüller, 2017).

4.2.1 Theoretical models through which may inequality affect economic growth

This section is dedicated to the presentation of theoretical background on mechanisms through which unequal distribution may affect economic output and development. Theoretical concepts formulated so far are summarized according to their positive or negative result on the relationship between inequality and output.

Theoretical models supporting the possibility that greater inequality might reduce growth:

Theory of endogenous fiscal policy: this theory can be described as a process when greater inequality becomes unacceptable for voters and has an effect on public policy through the election process. This situation leads to higher taxation and regulation which cause a higher risk for business, attenuate incentives to invest, and therefore economic growth (Bertola, 1993; Alesina and Rodrik, 1994; Persson and Tabellini, 1994; Perotti, 1996). Extreme inequality may also result to social unrest and political instability according to Alesina and Perotti (1996), Bénabou (1996) and Keefer and Knack (2002) or undermining the legal system (Glaeser et al. 2003), by promoting expensive fiscal policies (Perotti 1993), and by inducing an inefficient state bureaucracy (Acemoglu et al. 2011).

Theory of imperfect capital markets: Assumption of imperfect capital markets implies that individuals with lower wealth, income, or social background have reduced or more expensive (loan) possibilities for worthwhile investments (Galor and Zeira, 1993). In such an environment, individuals decide about their investment according to a rational comparison of returns from productive factors with related costs. In this situation, lower parts of the distribution, mainly poor are disqualified, and cannot afford investments with following increased return. The best example of an imperfect capital market assumption is education. Human capital is indivisible, in other words, attached to and limited by one person (Weil, 2013). If the poor cannot afford the fees, even though the rate of return on education (to both the individual and society) is high. The economy does not reach full potential and underinvestment decreases the potential of economic growth as in the case of perfect capital markets (OECD, 2015). This theory is very influential and led to further literature on social mobility and inequality of opportunities (Banerjee and Newman, 1993; Fershtman et al., 1996; Owen and Weil, 1998; Galor and Moav 2004; and Hassler et al., 2007). The human capital channel is examined deeper in the following Subchapter 4.3.

Theory of minimum critical amount of domestic demand: This theory is based on the hypothesis that the adoption of advanced technologies depends on a minimum critical amount of domestic demand which might not be sufficient if the poorer part of society have insufficient resources. This theory originates from work by Murphy et al. (1989) applied on the first stages of industrial take-off. The domestic demand channel has recently been put forward again by OECD (2015) when applied on present development.

Theoretical models supporting the possibility that greater inequality might increase growth:

High inequality provides incentives to work harder and undertake risks to take advantage of high rates of return: According to this theory inequality promotes growth by fostering incentives for innovation and entrepreneurship (Lazear and Rosen 1981) Another argument of this theory claims that if highly educated people are much more productive, then high differences in rates of return may encourage more people to seek education (Mirrlees, 1971).

Higher inequality fosters aggregate savings and consequently stimulate capital accumulation: because the rich have a lower propensity to consume (Kaldor, 1955;

Bourguignon, 1981). Higher inequality, in favour of the wealth of rich, may promote growth by fostering aggregate saving (Kuznets 1955; Kaldor 1955) which promotes the realization of high-return projects (Rosenzweig and Binswanger 1993) or by stimulating R&D (Foellmi and Zweimüller 2006).

4.2.2 Empirical results follow improvement in data and methodology)

The empirical literature on how inequality may affect economic growth showed contradictory results in the last decades. By the time and increasing complexity of estimating approaches, results seem to converge to the negative effects of inequality on economic growth in recent years. In this section, we focus rather on the chronological summary of results in this field of research.

Cross-sectional datasets: In the early 1990, theoretical models formalizing a negative effect of wealth inequality on economic growth attracted considerable attention. Starting serious empirical research was based on the first comparable international inequality databases. Models based on cross-sectional data explain variations between countries and appear to be quite sensitive to the inclusion of regional dummies, and sample selection. As Voitchovsky (2005) argues this approach results in the conclusion that inequality and economic growth are inversely related. In that time, several scientific works provide support for the idea that inequality is harmful for growth (Alesina and Rodrik 1994; Persson and Tabellini 1994; Deininger and Squire 1996), Deninger and Squire (1995), Deninger and Squire (1998), Clarke (1995), Birdsall and Londono (1997), Castello and Domenech (2002), Keefer and Knack (1995), Perotti (1996).

Panel structures and advanced methodology: Datasets have gradually developed to the panel structures with a wide sample of countries. The research based on panel approach does not support such a clear-cut relationship between inequality and economic growth as cross-sectional analysis (Deininger and Squire, 1996). There emerged studies resulting in the positive impact of inequality on economic growth for mainly advanced economies (Li and Zou, 1998, Forbes, 2000, Deninger and Olinto, 2000). Research differentiating rich and poor countries dimensions shows that the impact of inequality on growth is positive for rich countries and negative in the case of developing regions (Barro, 2000, Castelló, 2010). Banerjee and Duflo (2003) propose that a lack of consistency in the results is due to the fact that empirical studies estimate a linear model, whereas the true relationship is not linear.

Recent research: In the last years, the discussion about how inequality may affect economic growth has accelerated and became more complex with methodology trying to overcome shortcomings of previous studies. The next step in the field of income inequality brought Voitchovsky (2005), who states that previous empirical studies have used single aggregate indicators of inequality (Gini coefficient) which masks the differing effects of the lower and upper part of the income distribution on growth. She finds that inequality at the top of the distribution is positively related and inequality at the bottom of the distribution is negatively related to subsequent economic growth. That is why many of the positive mechanisms can be linked to inequality at the upper end of the income distribution, while many of the negative mechanisms are associated with inequality further down the distribution. The uncertainty about which aspect dominates persists (Voitchovsky, 2005).

Halter et al. (2014) contribute to the discussion with a simple theoretical model to study how changes in inequality affect economic growth over different time horizons. They find that higher inequality helps economic performance in the short run, but it reduces the growth rate of GDP per capita farther in the future. This can be explained as an effect of different channels between inequality and growth present in the short and long run. The long-run (or total) effect of higher inequality tends to be negative.

Verification of another influential channel between inequality and growth - redistribution, was conditioned by compilation of the Standardized World Income Inequality Database (Solt, 2009) which contains market (pre-tax and transfer) and net (post-tax and transfer) inequality data. This database was an incentive to Ostry et al. (2014) to extend usual inequality models and identify the direct effects of both inequality and redistribution on growth. They find that redistribution appears generally benign in terms of its impact on growth. Only when redistribution is very large, there is an evidence that it may have direct negative effect on the durability of growth. What is more, by controlling for the effect of redistribution they reveal that lower net inequality is strongly and robustly correlated with faster and more durable growth (Ostry et al., 2018). The hypothesis that more equal counties have significantly longer growth spells was already a result of earlier work by Berg and Ostry (2011).

Interesting stream of literature describing the effect of inequalities on economic growth through demand induced innovations is provided by Foellmi and Zweimüller (2003), who were inspired by the seminal work of Schmookler (1966). Authors claim that change in the distribution of income affects the incentive to innovate and so enhance the long-run growth. Firstly, they found that less inequality tends to discourage the incentive to innovate. But in later work, they explain that on the one hand, innovations are fostered if rich consumers are willing to pay high prices for new products, and on the other hand, profitable innovations require sufficiently large markets. So finally, when innovators have a large productivity advantage over traditional producers a higher extent of inequality tends to increase innovators' prices and mark-ups. When this productivity gap is small, however, a redistribution from the rich to the poor increases market size and speeds up growth (Foellmi and Zweimuller, 2017).

4.3 Human capital accumulation theory and inequality

The current literature converges to the conclusion that the channel through which inequality affects economic growth in advanced countries the most is the channel of human capital accumulation as a consequence of imperfect capital markets (OECD, 2015; Halter et al., 2014; Brueckner and Lederman, 2018; Ostry et al., 2018). In the following section, we present theoretical and empirical studies which follow the original contribution of Galor and Zeira (1993). Galor and Zeira describe the linkage between income distribution and macroeconomic statistics through unequal investment in human capital. Their general equilibrium model with overlapping generation is based on the capital market imperfections, the indivisibility of human capital, technological non-convexity, and initial distribution of bequest or wealth. Galor and Zeira are inspired by ideas of endogenous economic growth of Romer (1986) and Lucas (1988). Theory about the accumulation of human capital under the condition of imperfect capital markets contributes to the endogeneity of the processes described by Romer and Lucas. We explain in the next part how Galor and Zeira rather attribute the persistence of differences between economies to variation in endogenously determined investment in human capital.

Research from the seventies (Becker, 1975) reveals that if the borrowing under the condition of an imperfect capital market is costly, those with a large initial wealth do not need to borrow sources to invest and therefore have better access to investments to productive factors like human capital. On the other hand, the poor or households whose income is in lower parts of the income distribution are disqualified in investment process.

In the theory of human capital accumulation by Galor and Zeira (1993), the rational decision of an individual about investments in education is influenced by the imperfections of the capital market. The interest rate for individual borrowers is higher than for lenders.

Lenders are individuals who inherit the initial wealth in a form of bequest and so they possess an initial advantage. The clue assumption in this theory is the natural presence of indivisibility of human capital, in other words, the fact that education cannot be transferred from one individual to another (Becker, 1975). The stock of human capital in an economy is determined by the sum of individual years of education, so if the poor are disqualified, the economy does not reach its potential stock of productive human capital. As Loury (1981) indicates this unequal access to education may affect the aggregate amount of investment in human capital and thus the aggregate output. What is more, the model shows that the initial distribution of wealth would lead to persistence in future income inequalities and the gap between poor and rich will increase in further dynasties. This will consequently and continuously undermine the potential accumulation of human capital in economy.

The endogeneity of this model is based on the initial wealth distribution determining the future incomes through the decision under the assumption of imperfect market of capital and the market of education. Incomes that are driven by individual productivity would differ mainly in returns to education which are higher among workers with better or more scarce abilities. Better and more scarce abilities are in general connected to better education which the poor cannot afford, and the initial inequality persist and is carried to the long run (Galor and Zeira, 1993).

Hence, growth is affected by the initial distribution of wealth, or more specifically by the percentage of individuals who inherit a large enough wealth to enable them to invest in human capital. Authors of the theory highlight the importance of large enough middle class for future economic growth. So, they conclude that historically determined wealth distributions of countries imply different growth paths and that is why countries may even converge to different steady states (Galor and Zeira, 1993). The idea that higher inequality may result in under-investment in human capital among the poorer segments of society has also spurred a significant amount of research on the consequences of inequality on social mobility and the allocation of talents across occupations (Banerjee and Newman, 1993; Fershtman et al., 1996; Owen and Weil, 1998 and Hassler et al., 2007).

Later, the empirical work by Deininger and Squire (1998) strongly corresponds to the importance of initial wealth distribution as a determinant of future human capital accumulation. Authors find a strong negative relationship between initial inequality in the distribution of asset and long-term growth. Moreover, they reveal that inequality reduces income growth for the poor, but not for the rich. Because initial inequality hurts mainly the poor, the policies that increase aggregate investment and facilitate the acquisition of assets by the poor might be doubly beneficial for growth and poverty reduction, because initial land inequality has a significant effect on aggregate schooling attainment (Deininger, Squire, 1998).

Galor and Moav (2006) applied a similar principle in the theory explaining incentives for the encouragement of public education policies by capitalists during the process of industrialization. Based on the theory of return to education (Becker, 1975) and findings from Galor and Zeira (1993), they argue that capital accumulation in the process of industrialization gradually intensified the relative scarcity of skilled labour and generated an incentive for human capital accumulation. In other words, due to the complementarity between physical and human capital in production, the capitalists were among the prime beneficiaries of the accumulation of human capital by the masses. As long as the rate of return on human capital is higher than the rate of return on physical capital, the chosen level of investment in public education by capitalists is higher than 0. Once the rate of return to human capital equals the rate of return on physical capital, the chosen investment in public education is positive, and thus maximizes output per worker (Galor and Moav, 2006).

Later, the same authors support the idea that the inequality in land ownership adversely affects the emergence of institutions promoting human capital and thus attenuate the pace of transition to modern growth. Economies with equally distributed land implemented the public education earlier and benefited from the emergence of a skilled-intensive industrial sector accompanied with rapid process of development. In contrast, economies with unequal distribution of land ownership, the land abundance that was a source of richness in early stages, led in later stages of development to under-investment in human capital and unskilled-intensive industrial sector with lower growth (Galor and Moav, 2009). The principle of the different effect of inequalities according to country development level is elaborated well in a number of other empirical works (Barro, 2000; Forbes, 2000; Banerjee and Duflo, 2003) which is not necessarily based on the human capital accumulation.

Ostry et al. (2018) provide an evidence supporting the hypothesis that inequality's impact on growth works through not only higher education, but also increased life expectancy, and higher fertility. Moreover, de la Croix and Doepke (2003) argue that inequality increases the fertility of the poor and hence reduces human capital accumulation and per capita growth (Ostry et al., 2018).

Strong emphasis on the role of human capital in the channel from inequality to economic growth is provided by Costello (2010). His study uses rather a measure of human capital inequality instead of average years of education or education stock measures for economic analysis. The human capital Gini index is based on attainment levels among population quantiles from Barro and Lee (2001). Castelo and Domenech (2002) used the measure of human capital inequality to show that human capital inequality measure provides more robust results than income inequality measures in the estimation of standard growth and investment equations. The introduction of this measure into the study by Castelo reveals that, all other things being equal, a greater degree of human capital inequality increases fertility rates and reduces life expectancy, which in turn discourages the accumulation of human capital. Moreover, the adverse effect of human capital inequality on investment and growth is reinforced when individuals find it difficult to gain access to credit. Likewise, the paper indicates the negative effect of income and human capital inequality on economic growth, both in the sample as a whole and in the low and middle-income economies, an effect that vanishes or becomes positive in the higher-income countries. (Castello, 2010).

In contrary, the recent paper by Brueckner and Lederman (2018) estimates how does the effect of inequality on transitional growth differs depending on countries development as well. They control for countries' initial incomes and results from their regressions show that in low-income countries transitional growth is boosted by greater income inequality and in high-income countries inequality has a significant negative effect on transitional growth. Brueckner and Lederman (2018) take theory defined by Galor and Zeira (1993) seriously. Evidence that their empirical findings are consistent with the model comes from estimates of the relationship between inequality and human capital. They use a panel of world countries between 1970 and 2010. Their estimations reveal that coefficients on inequality are significantly positive while the coefficients on the interaction between inequality and initial income are significantly negative. They conclude that the inequality undermines growth in advanced economies and that for poor countries initial inequality affects economic growth positively. Secondly, they find the least-squares estimation of the effect of inequality on human capital suffers from negative endogeneity bias. This negative bias is consistent with the Galor and Zeira (1993) model. Higher average income leads to an increase in the average human capital in the population as more people accumulate human capital inequality decreases. So that the model where inequality determines human capital accumulation the coefficient of the interaction between inequality and initial income is higher when accounting for endogeneity bias of human capital (Brueckner and Lederman, 2018).

The hypothesis that the inequality has a significantly negative impact on growth through the channel of human capital, mainly in advanced countries, is well documented in a study by OECD (2015). Children of individuals with lower social backgrounds or lower proficiency are disqualified in the education system to trace the worse track of lower quality schools or to afford fewer years of education and so to accumulate a lower amount of human capital.

Their report is based on the best available sample of very detailed data among OECD countries. The study uses very detailed microdata on income distribution, controls for the country in the time-invariant characteristics and use the advantage of individual-level data from OECD Adult Skills Survey (PIAAC) with statistics about parent education background as a proxy of socio-economic background to control for intergenerational social mobility (e.g. Causa and Johansson, 2009; and OECD, 2011b) and get real in-country causality between inequality and economic growth. They introduce proxy for social background to get rid of the bias in the form of parents' education effect on the education of their children which seems to be a strong determinant. Results imply that social mobility is the key indicator for future economic growth because the wider is income inequality, the lower is the chance that low-income households invest in education. Inequality harms growth through the channel of human capital: the wider is income inequality, the lower is the chance that low-income households invest in education (OECD, 2015).

Furthermore, the negative effect of inequality on growth is determined by the lower part of the income distribution, which is not only the poorest, but the bottom 40% of actual income earners. This is explained by the low intergenerational mobility. The probability of tertiary education decreases with inequality only in the case of low social background individuals. An increase in inequality of around 6 Gini points would lower the probability of individuals with parents of low educational background being in tertiary education by around 4 percentage points. Inequality is also associated with a significant increase in the probability that low PEB individuals attain at most the lower secondary education (OECD, 2015).

There are two major reasons which may lead agents to make different human capital investment choices: personal attitudes and talents (ability) and costs involved in investing today in order to obtain a future benefit (intertemporal discount rate). Since the returns to schooling are decreasing, individuals from disadvantaged families will stop accumulating schooling earlier because, with imperfect capital markets, they face higher discount rates. By accumulating less schooling, they will earn lower wages and provide lower family background to their offspring, thus perpetuating inequality.

5 Aim of the dissertation thesis

This dissertation thesis aims to contribute to the existing literature on the linkages between inequality, human capital formation and economic growth by using the advantages of the non-parametric data envelopment analysis (DEA). Literature about the impact of inequality on high skills often provides ambiguous results. We believe that the construction of the world production frontier and its contribution to the accumulation of high skills could provide new arguments this this discussion. For this reason, we modify two types of non-parametric decompositions to reveal, the contribution of inequality on the accumulation of high-skilled labour and the contribution of high-skilled labour to productivity growth.

Previous chapters provide a theoretical background for our two-step analysis. We formulate a simplified model, where the inputs of capital stock, low- and high- skilled labour produce economic output in the form of real gross domestic product and take into consideration also an unpleasant output in the form of the Gini indicator. Real GDP represents the level of output and the Gini index describes the distribution of output among the population.

In the first step of our analysis, we follow the literature about the negative effect of inequality on the accumulation of human capital. Inspired by work based on models by Galor and Zeira (1993) and Galor and Moav (2004), we search for contribution of a change in the Gini index on the accumulation of high-skilled labour. The second part of the analysis follows the growth literature, which estimates positive effect of high-skilled labour on economic (Lutz et al., 2008; Flabbi and Gatti, 2018).

The first hypothesis is that inequality contributes negatively to the accumulation of higher skills and that this effect is more significant among developed countries. The second hypothesis aims to confirm the positive effect of higher skills on economic growth and that the high skills are more significant determinant of economic growth for developed countries.

The advantage of DEA in our case is two-fold. The first is the ability to compose the world technological frontier created from efficient countries in a multi-input and multi-output dimensional space. The efficiency of other countries is represented by their radial distance from the efficient benchmark on the frontier. In simplified language, in DEA we measure the location of a certain point, or at least the distance of certain point, relative to the efficient frontier. The second advantage focuses attention on the movement of this efficient frontier between two time periods. Thus, the inter-temporal analysis follows the movement of a certain country or point in the multidimensional space relative to the simultaneously moving technological frontier. This dissertation thesis modifies two types of inter-temporal decompositions which follow this envelopment concept. In general, intertemporal DEA decomposition decomposes the development of a certain output (economic productivity) or input (high-skilled labour) into the contribution of the movement of a certain point towards the efficient frontier, the movement of the efficient frontier itself and the movement along the efficient frontier, further broken down into the contribution of the input mix and the output mix.

To be specific, we modify two nonparametric decompositions based on the DEA analysis by Henderson and Russell (2005) and Färe et al. (2018). Henderson and Russell's model introduces the decomposition of economic productivity (output) with the aim of finding how the human capital change contribute to it. Our modification of their model is based on the introducing the two inputs of high- and low- skilled labour (according to ISCED educational levels) instead of labour augmented by the Mincerian measure of human capital (Hall and Jones, 1999). The main difference is in the fact that Henderson and Russell use one composite input and one composite output model, and our analysis uses multiple inputs with a single output, which is standard in the nonparametric approach. Our motivation for such a modification comes from the research by Lutz et al. (2008) or Flabbi and Gatti (2018), who base the analysis of economic growth on detailed data about the level of education instead of literature based on Mincerian returns to education. Using the recent dataset of Lutz et al. (2018), we find that the contribution of high-skilled labour to productivity growth.

In the second model, we modify the nonparametric decomposition by Färe et al. (2018), which we use to reveal the contribution of increasing inequalities to the accumulation of high-skilled labour. The idea for this decomposition comes from literature based on the theory of Galor and Zeira (1993), who argue that under the imperfect capital markets condition, increasing inequality decreases investment to education and so it harms the accumulation of human capital mostly in advanced countries. The decomposition by Färe et al. follows the aim of decomposing the development in input (high-skilled labour) by the contribution of output (inequality).

6 Methodology

As already mentioned in the Chapter 5, we will use advantage of non-parametric approach to contribute into the literature about the linkages between inequality, human capital accumulation and economic growth. The first part of the methodology section explains the reason we use a nonparametric approach and in what way it contributes to present discussion. The following part is dedicated to the introduction of basic data envelopment models and intertemporal analysis. The last two sections of this chapter are dedicated to the modification of decompositions proposed by Henderson and Russell (2005) and by Färe et al. (2018).

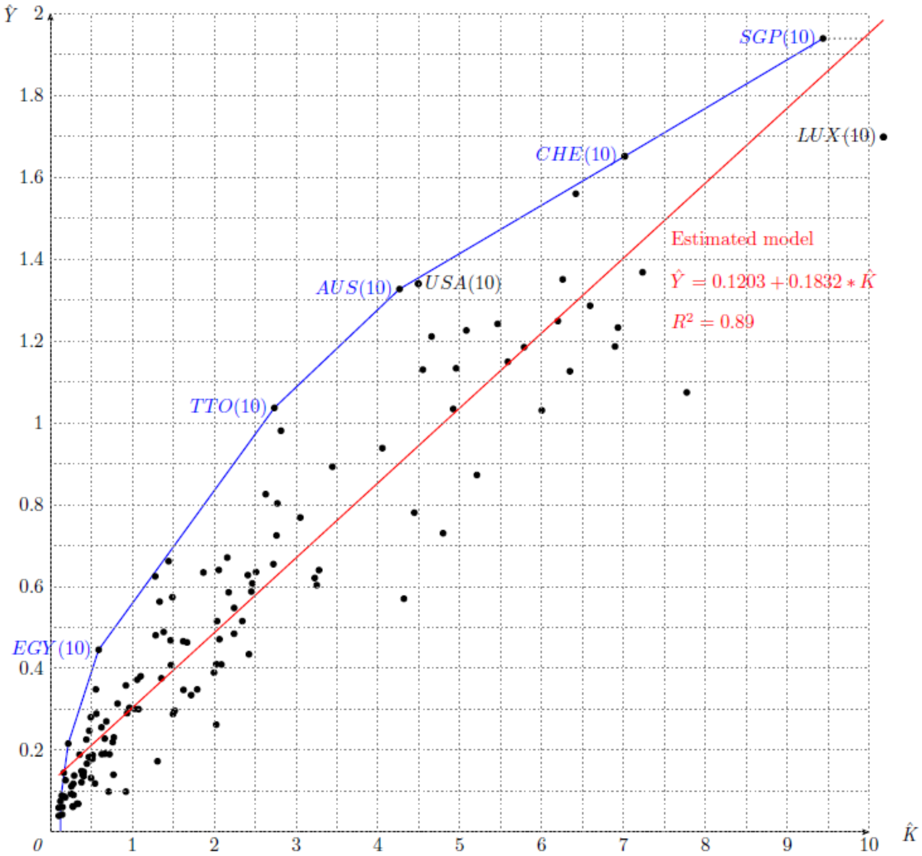
6.1 Motivation for nonparametric approach

The principal difference between parametric and nonparametric approaches relates to the production frontier and technology function. The parametric approach uses different estimators to find the best parameters in aim to define general technology which would fit the sample of empirical data with the lowest possible sum of deviations. On the other hand, the nonparametric DEA concept envelopes the sample of data with a convex envelopment composed of efficient units regardless of the technology function. Efficiency is derived from the radial distance of an economy relative to its frontier benchmark. Nonparametric methods envisage a single worldwide frontier at a point in time with most of the countries operating (inefficiently) below the frontier. This concept has certain weaknesses resulting from heterogeneity. Mainly, the sensitivity on outliers and assumption of comparable individual technological background of compared countries could have implausible effect on efficient frontier composition and consequently on individual results in the basic model. Henderson and Russell (2005) find the argumentation in favour of nonparametric methods via criticism by Quah (1993), who argues that convergence analyses based on standard regression methods are focusing on the first moments of the distribution and that cannot adequately address the convergence issue better described by the intertemporal movement of the efficient frontier.

Later, a similar argumentation is adopted by Luptáčik and Mahlberg (2011), who find two approaches to productivity analysis, namely the neoclassical approach and the frontier approach. Both approaches track changes in productivity as the output-input ratio of an economy, but their methods are quite distinct. The neoclassical approach imputes productivity growth to factors but cannot distinguish between a movement towards the frontier and a movement of the frontier. The frontier approach allows us decomposing productivity growth into a movement of the economy towards the frontier and a shift of the frontier.

The simple distinction between parametric and nonparametric approaches is described well in Figure 6.1. For better understanding, we used simple one output and one input model as in the Henderson and Russell (2005) paper. The single input is represented by the ratio of capital stock divided by human capital augmented labour ($\widehat{K}$) and the output is represented by GDP divided by human capital augmented stock of labour ($\widehat{Y}$). The figure describes deterministically defined efficient frontier by data envelopment analysis (blue line) and by a simple OLS regression as a representation of a stochastic approach (red line). As we argue, the DEA technological frontier is defined by the efficient envelopment. The principle behind the frontier

Figure 6.1 Distinction between parametric and non-parametric approach (data from 2010)



Source: Author's calculations based on the methodology of Henderson Russell (2005) and data from Penn World tables 9.2 composition is explained in the later section. Among the high performing region (upper-right part of figure), efficient countries are Singapore, Switzerland or Australia and the efficient benchmark for lower-performing region are Trinidad and Tobago or Egypt. On the other hand, if we would like to incorporate the technological gap in the parametric approach, we would need to introduce a variable holding the information about distance from the benchmark countries. It is usually done by a proxy variable that determines the technological level of each country as in Lutz et al. (2008), who used proxy of the share of country GDP per capita on the GDP per capita of the top-performing country. Another advantage of a non-parametric approach is the possibility to use multiple inputs and multiple outputs to find a single measure of efficiency score.

The nonparametric approach, which takes the advantage of shifting technology or world aggregate production frontier, is commonly used for analysis in productivity convergence literature (Kumar and Russell, 2002; Henderson and Russell, 2005; Badunenko et al., 2008, 2013; Walheer, 2016). Nonparametric decomposition based on the pioneering contribution of Färe et al. (1994) allows us to decompose the labour productivity growth into the contribution of several determinants, which follows the movement of DMU along the efficient frontier. Kumar and Russell (2002) applied this method to decompose contribution of (1) technological change as a shift of the world production frontier, (2) technological catch-up as movements toward or away from the frontier, and (3) physical capital accumulation as movements along the frontier. Later, Henderson and Russel (2005) extended this tripartite decomposition by a factor of (4) human capital accumulation. Additionally. Later, Färe et al. (2018) provides a different approach to decomposition. They decompose contributions of multiple factors to the one of inputs, in particular to change in labour stock.

In the following sections, we go through the non-parametric methodology. Firstly, we introduce a simple data envelopment analysis model methodology. Later, the intertemporal analysis by the Malmquist index is described. And finally, we explain modifications of Henderson and Russell's (2005) decomposition and Färe et al. (2018) decomposition as a methodological concept used in the empirical part of the dissertation thesis.

6.2 Basic DEA model

So far, we did not answer the question of, how is the world efficient frontier identified. The primary aim of DEA is a simple measurement of efficiency in case of multiple inputs and multiple outputs. Usually, the score of multidimensional indices and rankings is based on the a priori selection of weights, which should mirror the relative importance of variables entering composite index. Following the argumentation of Luptáčik (2010) in such a case, each country would choose weights maximizing its score. This mechanism of optimal weights selection or assignment DEA solves. DEA, in other words, searches for optimal weights to be assigned to each output and every input to maximize the efficiency score as a ratio of virtual output and virtual input, which are characterized as a weighted sum of outputs and a weighted sum of inputs. So that if a certain set of wights is assigned, any country is efficient or inefficient. DEA also allows several sets of optimal weights to be in one model under the assumption of variable returns to scale. It is so if the sum of weights is restricted.

As we already mentioned, in DEA, the efficiency is measured as a ratio of virtual outputs and virtual inputs (6.1, 6.2). The advantage of DEA is also that the relative efficiency score is not affected by the choice of different measurement units, which is referred to as "unit invariance". Organization under the study is called the decision-making unit (DMU). Generically, DMU is regarded as an entity responsible for converting inputs into outputs and whose performances are to be evaluated. In our case DMUs are world countries. Let suppose there are n DMUs: DMU_1, DMU_2, ..., and DMU_n. Later, suppose m input items and s output items which are selected numerical values with data available for each input and output. In principle, in case of oriented DEA models, it is preferable to reach a certain level of outputs with a lower level of inputs and anther way around, it is preferable to reach a certain level of inputs with a higher level of outputs. For formalization of the DEA model, let the input and output data for DMU_j be $(x_{1j}, x_{2j}, \dots, x_{mj},)$ and $(y_{1j}, y_{2j}, \dots, y_{sj},)$, respectively. For simplicity, let call input data matrix **X** and the output data matrix **Y** (Cooper et al., 2007).

Pioneering work by Charnes, Cooper and Rhodes (1978) introduces the method of DEA to measure the efficiency of DMUs with multiple inputs and multiple outputs in the absence of market prices. They formalize the virtual input and virtual output for each DMU by (yet unknown) weights (v_i) and (u_r):

$$Virtual\ input = v_1 x_{1o} + \cdots + v_m x_{mo} \tag{6.1}$$

$$Virtual\ output = u_1 y_{1o} + \cdots + u_s y_{so} \tag{6.2}$$

Given the data, we measure the efficiency of each DMU once and hence need n optimizations, one for each DMU_j to be evaluated. Let the DMU_j to be evaluated on any trial to be designated as DMU_o where o ranges over $1, 2, \ldots, n$. We solve the following fractional programming problem to obtain values for the input "weights" (v_i) $\{i = 1, \ldots, m)$ and the output "weights" (u_r) $(r = 1, \ldots, s)$ as variables.

$$(FP_o) \quad \max_{\boldsymbol{u},\boldsymbol{v}} \qquad \theta = \frac{Virtual\ output}{Virtual\ input} = \frac{u_1 y_{1o} + u_2 y_{2o} + \cdots + u_s y_{so}}{v_1 x_{1o} + v_2 x_{2o} + \cdots + v_m x_{mo}} \tag{6.3}$$

$$subject\ to \qquad \frac{u_1 y_{1o} + u_2 y_{2o} + \cdots + u_s y_{so}}{v_1 x_{1o} + v_2 x_{2o} + \cdots + v_m x_{mo}} \leq 1\ (j = 1, \ldots, n) \tag{6.4}$$

$$v_1, v_2, \ldots . v_m \geq 0 \tag{6.5}$$

$$u_1, u_2, \ldots . u_s \geq 0 \tag{6.6}$$

The constraints mean that the ratio of "virtual output" vs. "virtual input" should not exceed 1 for every DMU. The objective is to obtain weights (v_i) and (u_r) that maximize the ratio of DMU_o, the DMU being evaluated. By virtue of the constraints, the optimal objective value θ^* is at most 1. Mathematically, the nonnegativity constraint (6.5) is not sufficient for the fractional terms in (6.4) to have a positive value. We do not treat this assumption in explicit mathematical form at this time. Instead we put this in managerial terms by assuming that all outputs and inputs have some nonzero worth and this is to be reflected in the weights u_r and v_i being assigned some positive value (Cooper et al., 2007).

Later, all data are assumed to be nonnegative but at least one component of every input and output vector is positive. We refer to this as semi-positive with a mathematical characterization given by $\boldsymbol{x}j \geq \boldsymbol{0}, \boldsymbol{x}j \neq \boldsymbol{0}$ and $\boldsymbol{y}j \geq \boldsymbol{0}, \boldsymbol{y}j \neq \boldsymbol{0}$ for $j = 1, \ldots, n$ where small letters in bold denote vectors. Therefore, each DMU is supposed to have at least one positive value in both input and output vector. We will call a pair of such semi-positive input $\boldsymbol{x} \epsilon R^m$ and output $\boldsymbol{y} \epsilon R^s$ an activity and express them by the notation $(\boldsymbol{x}, \boldsymbol{y})$. The components of each such vector pair can be regarded as a semi-positive orthant point in $(m + s)$ dimensional linear vector space in which the superscript m and s specify the number of dimensions required to express inputs and outputs, respectively. (Cooper et al., 2007). Bold lower-case letters represent vectors.

Following Cooper, Seiford and Tone (2007), based on the matrix (X, Y), the CCR model is transformed from a fractional program to linear program. They formulate a linear program (LP) problem with row vector $\boldsymbol{v}$ for input multipliers and row vector $\boldsymbol{u}$ as output multipliers. These multipliers are treated as variables in the following LP problem (Multiplier form):

$$(LP_o) \quad \max_{\boldsymbol{u},\boldsymbol{v}} \qquad \boldsymbol{u}\boldsymbol{y}_{\mathbf{0}} \tag{6.7}$$

$$subject\ to \qquad \boldsymbol{v}\boldsymbol{x}_o = 1 \tag{6.8}$$

$$-\boldsymbol{v}X + \boldsymbol{u}Y \leq \mathbf{0} \tag{6.9}$$

$$\boldsymbol{v} \geq \mathbf{0}, \boldsymbol{u} \geq \mathbf{0} \tag{6.10}$$

The dual problem of (LP_o) (Appendix A.4 of Cooper et al., 2007) is expressed with a real variable θ and a nonnegative vector $\boldsymbol{\lambda} = (\lambda_1, \ldots, \lambda_n)^T$ of variables as follows ([Envelopment form]):

$$(\text{DLPo}) \quad \min_{\theta,\boldsymbol{\lambda}} \qquad \theta \tag{6.11}$$

$$subject\ to \qquad \theta\boldsymbol{x}_o - X\boldsymbol{\lambda} \geq \mathbf{0} \tag{6.12}$$

$$\boldsymbol{y}_o - Y\boldsymbol{\lambda} \leq \mathbf{0} \tag{6.13}$$

$$\boldsymbol{\lambda} \geq \mathbf{0} \tag{6.14}$$

(DLPo) has a feasible solution $\theta = 1, \lambda_o = 1, \lambda_j = 0\ (j \neq o)$. Hence the optimal θ, denoted by θ^*, is not greater than 1 On the other hand, due to the nonzero (i.e., semi-positive) assumption for the data, the constraint (6.13) forces $\boldsymbol{\lambda}$ to be nonzero because $\boldsymbol{y_o} \geq \mathbf{0}$ and $\boldsymbol{y_o} \neq \mathbf{0}$. Hence, from (6.12), θ must be greater than zero. Putting this all together, we have $0 < \theta^* \leq 1$. Now we observe the relation between the production possibility set P and (DLPo). The constraints of (DLPo) require the activity $(\theta\boldsymbol{x}_o, \boldsymbol{y_o})$ to belong to P, while the objective seeks the minimum θ that reduces the input vector $\boldsymbol{x}_o$ radially to $\theta\boldsymbol{x}_o$ while remaining in P. In (DLPo), we are looking for an activity in P that guarantees at least the output level $\boldsymbol{y_o}$ of DMU_o in all components while reducing the input vector $\boldsymbol{x}_o$ proportionally (radially) to a value as small as possible (Cooper et al., 2007). Later, an optimal solution of the dual linear program of output-oriented model (DLPOo) can be derived directly from an optimal solution of input-oriented CCR model (DLPo) defined in (6.11) - (6.14) via:

$$\boldsymbol{\lambda} = \boldsymbol{\mu}/\eta\,, \quad \theta = 1/\eta \tag{6.15}$$

The output-oriented model attempts to maximize outputs while using no more than the observed amount of any input and is formulated as:

$$\text{(DLPOo)} \quad \max_{\eta,\boldsymbol{\mu}} \quad \eta \tag{6.16}$$

$$\textit{subject to} \quad \boldsymbol{x}_{to} - X\boldsymbol{\mu} \geq \boldsymbol{0} \tag{6.17}$$

$$\eta\boldsymbol{y}_o - Y\boldsymbol{\mu} \leq \boldsymbol{0} \tag{6.18}$$

$$\boldsymbol{\mu} \geq \boldsymbol{0} \tag{6.19}$$

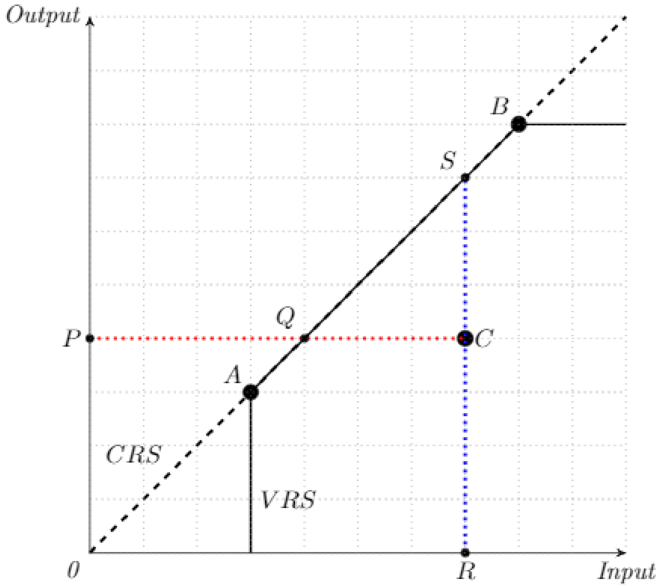
Later. optimal solution of output -oriented CCR model (6.16) - (6.19) relates to input-oriented CCR model (6.11) - (6.14) via:

$$\eta^* = 1/\theta^*, \quad \boldsymbol{\mu}^* = \boldsymbol{\lambda}^*/\theta^* \tag{6.20}$$

(Cooper et al., 2007).

For reconstruction of world production frontier, we use simple data envelopment model with constant returns to scale (CRS) by Charnes, Cooper and Rhodes (1978) – CCR model. For better understanding, we provide Figure 6.2 where are depicted efficient points A, B and one inefficient pint C. By the black dashed line is describes the model with CRS and solid line represent envelopment under the condition of VRS. Moreover, we present the measurement of output orientated CCR model shown in blue colour. The efficiency of point C under the input-oriented efficiency would be derived as RC/SC . Later, by red colour is depicted the measurement of the input-oriented model as PQ/PC. In the next sections, we use the output-oriented model (CCR-O) for the purpose of Henderson and Russell (2005) decomposition and, for Färe et al. (2018) decomposition, we employ model with input-orientation (CCR-I).

Figure 6.2 Basic DEA model with comparison between CRS and VRS and difference between input- and output-orientation



Source: Cooper, Seiford and Tone, 2007 with author's modifications

For solving DEA models, we the software Matlab with linprog order dedicated to linear optimization issue. We use Matlab for simple DEA models as well as for more complicated decomposition models. It is necessary to code our own program because the necessary features of intertemporal decompositions modifications are not provided by simple DEA solver software.

6.2.1 Inequality as an undesirable output

Inequality in the form of the Gini index is treated in our DEA analysis as undesirable output or so-called "bad" output. Because income inequality results from economic activity, we treat it as output even though, it enters the production of human capital of the next generation as potential inequality of opportunity (Atkinson, 2015). Following the social welfare function, inequality harms the welfare of society (Fleurbaey, 2009). Beyond measuring the level of GDP, it is needed to take into consideration also its distribution. This idea leads to theories about the trade-off between efficiency and equity (Nicola, 2013). Moreover, the government objective is to keep inequality on a certain level acceptable by society as noted previously in the theory of endogenous fiscal policy. The higher value of the Gini index corresponds to higher inequality in society and we need to incorporate this aspect into our DEA model in proper way. It is worth to mention that we could easily avoid this challenge by simple modification of inequality measure on the form of equality measure

$1 - Gini$ index. But we prefer usage of the original inequality index with more intuitive interpretation. Färe et al. (2018) decomposition already incorporates bad output in the form of pollution abatement. On the contrary to Färe et al., we treat inequality as a bad output with zero jointness to good output. Producing good outputs does not require producing bad outputs even though, the literature from Section 4.2.1 proposes that between inequality and economic growth exist certain kinds of direct relation. In general inequality enters only our input-oriented model in a way that it disqualifies the country to achieve high efficiency score if it has high Gini index, but the model searches for potential reduction in inputs while keeping a constant level of good and bad output. Concrete formulation of the model is composed as follows:

$$\text{(DLPo)} \quad \min_{\theta,\boldsymbol{\lambda}} \quad \theta \tag{5.22}$$

$$\textit{subject to} \quad \theta \boldsymbol{x}_o - X\boldsymbol{\lambda} \geq \mathbf{0} \tag{5.23}$$

$$\boldsymbol{Gi}_o - Gi\boldsymbol{\lambda} \geq \mathbf{0} \tag{5.24}$$

$$\boldsymbol{y}_o - Y\boldsymbol{\lambda} \leq \mathbf{0} \tag{5.25}$$

$$\boldsymbol{\lambda} \geq \mathbf{0} \tag{5.26}$$

Moreover, Cooper, Seiford and Tone (2007) propose several methodological procedures on how to design the DEA model with undesirable outputs. We mostly follow the model by Färe at all. (2018) and modify simple input-oriented CCR model 6.22-6.26 to introduce the Gini index ($\boldsymbol{Gi}_o$ is a vector of the Gini index for country o and Gi represent matrix of the Gini indices).

6.3 Intertemporal analysis

The main advantage of a non-parametric approach is in its natural feature of differentiation on how can be intertemporal progress (regress) divided into change in efficiency (movement towards efficient frontier) and the shift of the technically efficient frontier. The first important step to intertemporal decompositions in the next Section 6.4 and 6.5 is based on the simple Malmquist index whose methodology is explained in the following paragraphs.

6.3.1 Malmquist index

Following the methodology described in Cooper, Seiford and Tone (2007), the Malmquist index evaluates the productivity change of a DMU between two time periods. It is an example of "comparative statics" analysis. Malmquist index is defined as the product of Catch-up and Frontier-shift terms. The catch-up term relates to the degree to which a DMU improves or worsens its efficiency, while the frontier-shift term reflects the change in the efficient frontiers between the two time periods. We deal with a set of n DMUs $(\boldsymbol{x}_j, \boldsymbol{y}_j)$ $(j = 1. \ldots, n)$ each having m inputs denoted by a vector $\boldsymbol{x}_j \epsilon R^m$ and q outputs denoted by a vector $\boldsymbol{y}_j \epsilon R^q$ over the periods 1 and 2. We assume $\boldsymbol{x}_j > \boldsymbol{0}$ and $\boldsymbol{y}_j > \boldsymbol{0}$. The notations $(\boldsymbol{x}_o, \boldsymbol{y}_o)^1 = (\boldsymbol{x}_o^1, \boldsymbol{y}_o^1)$ and $(\boldsymbol{x}_o, \boldsymbol{y}_o)^2 = (\boldsymbol{x}_o^2, \boldsymbol{y}_o^2)$ are employed for designating $DMUo$ $(o = 1, \ldots, n)$ in periods 1 and 2 respectively. We now develop the numerical measures for which we employ the following notation. The efficiency score of DMU $(\boldsymbol{x}_o, \boldsymbol{y}_o)^{t_1}$ measured by the frontier technology t_2 is represented by efficiency scores as in the simple CCR-O model from the previous sub-section:

$$\delta^{t_2}((\boldsymbol{x}_o, \boldsymbol{y}_o)^{t_1})(t_1 = 1, 2 \; and \; t_2 = 1, 2) \tag{6.27}$$

Using this notation, the catch-up (C) effect can be expressed as:

$$C = \frac{\delta^2((\boldsymbol{x}_o, \boldsymbol{y}_o)^2)}{\delta^1((\boldsymbol{x}_o, \boldsymbol{y}_o)^1)} \tag{6.28}$$

and the frontier-shift effect (F) is represented by

$$F = \left[\frac{\delta^1((\boldsymbol{x}_o, \boldsymbol{y}_o)^1)}{\delta^2((\boldsymbol{x}_o, \boldsymbol{y}_o)^1)} \times \frac{\delta^1((\boldsymbol{x}_o, \boldsymbol{y}_o)^2)}{\delta^2((\boldsymbol{x}_o, \boldsymbol{y}_o)^2)}\right]^{1/2} \tag{6.29}$$

As the product of C and F, we obtain the following formula for the computation of MI, the Malmquist Index,

$$MI = \left[\frac{\delta^1((\boldsymbol{x}_o, \boldsymbol{y}_o)^2)}{\delta^1((\boldsymbol{x}_o, \boldsymbol{y}_o)^1)} \times \frac{\delta^2((\boldsymbol{x}_o, \boldsymbol{y}_o)^2)}{\delta^2((\boldsymbol{x}_o, \boldsymbol{y}_o)^1)}\right]^{1/2} \tag{6.30}$$

Expression 6.30 gives interpretation of MI as the geometric mean of the two efficiency ratios: the one being the efficiency change measured by the period 1 technology and the other the efficiency change measured by the period 2 technology. As can be seen from these formulas, MI consists of four terms: $\delta^1((\boldsymbol{x}_o, \boldsymbol{y}_o)^1), \delta^2((\boldsymbol{x}_o, \boldsymbol{y}_o)^2)$, $\delta^1((\boldsymbol{x}_o, \boldsymbol{y}_o)^2)$ and $\delta^2((\boldsymbol{x}_o, \boldsymbol{y}_o)^1)$. The first two are related to the measurements within the same time period with $t = 1$ or $t = 2$, while the last two are for intertemporal comparison.

$MI > 1$ indicates progress in the total factor productivity of the DMUo from period 1 to period 2. While $MI = 1$ and $MI < 1$ respectively result indicates the status quo and deterioration in the total factor productivity (Cooper et al., 2007).

Figure 6.3 describes the intertemporal analysis in theoretical input-oriented model of one output and output technology with VRS. Point P represents $(x_o, y_o)^1$ production in the first period and point Q equivalently represents $(x_o, y_o)^2$ production in the second period. So that, Malmquist index can be graphically formalized as in the textbook by Cooper, Seiford and Tone (2007):

$$MI = Catch\,up \times Frontier\ shift = \frac{AP}{BQ} \times \sqrt{\frac{BF}{AC}\frac{BD}{AE}} \tag{6.31}$$

Catch up effect can be very generally expressed by blue lines on Figure 6.3. As the ratio of efficiency scores from the first and second period we provide geometrical definition:

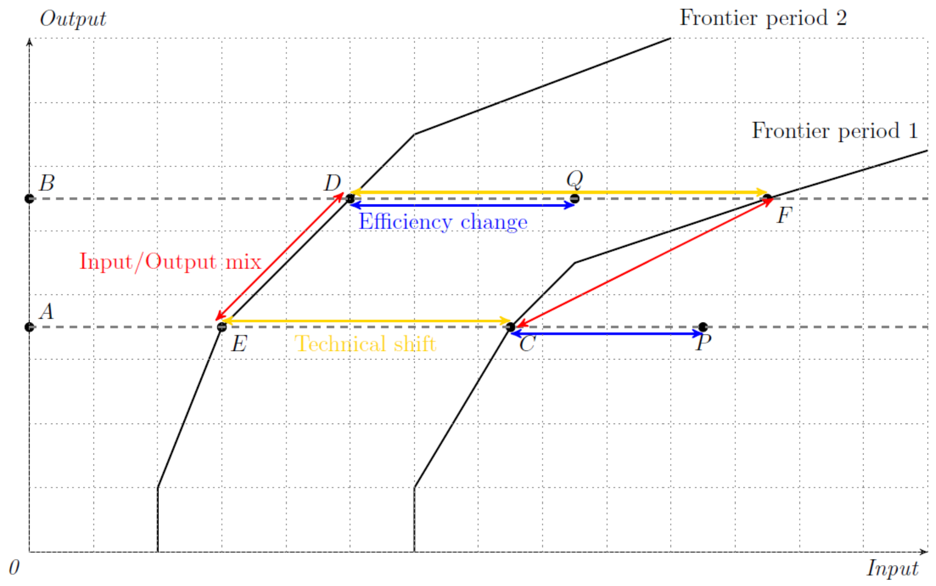
$$Catch\,up = \frac{BD}{BQ} \bigg/ \frac{AC}{AP} \tag{6.32}$$

Frontier shift generally depicts movement following the geometric average of yellow elements. Yellow elements describe the mean shift of the frontier between two time periods. The second part of expression 6.33 explains geometric average of the ratio of efficiency score of the period 1 relative to the technology of period 1 to efficiency score of the period 1 relative to the technology of period 2 multiplied by the ratio of efficiency score of the period 2 relative to the technology of period 1 to efficiency score of the period 2 relative to technology of period 2. The third part of 5.33 is the same as 6.29 expression.

$$Frontier\ shift = \sqrt{\frac{AC/AP}{AE/AP} \times \frac{BF/BQ}{BD/BQ}} = \sqrt{\frac{AC}{AE} \times \frac{BF}{BD}} \tag{6.33}$$

We see that the Malmquist index can describe the movement toward the frontier and the shift of the frontier over time, but it lacks an explanation of the movement along the frontier expressed by red elements on Figure 6.3. This feature is further extended in the following sections.

Figure 6.3 Malmquist index anatomy explained on input-oriented model with VRS

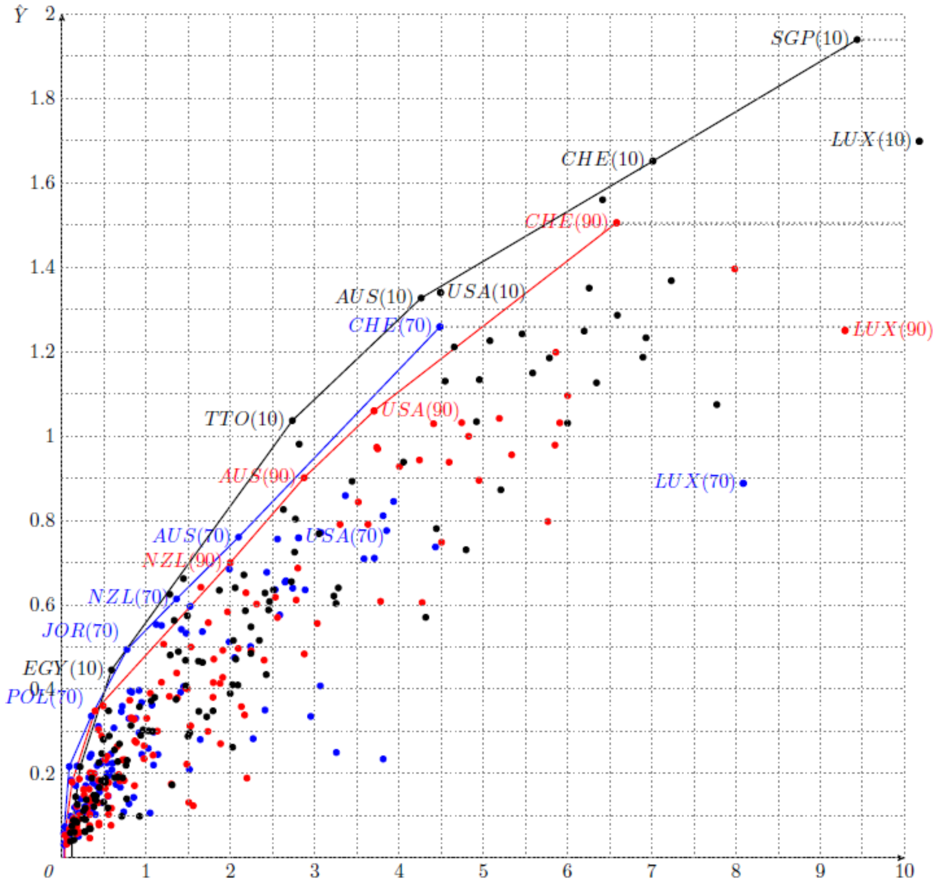


Source: Cooper, Seiford and Tone, 2007 with author's modifications

The shift of technology frontier may be better explained on real data example of one output and one input model with VRS based on Henderson and Russell (2005) methodology. Hence, they decompose productivity into the contribution of capital, labour, and human capital stock changes, but their technology enters only one input and one output in the form of economic output per efficient unit of labour ($\hat{Y}$) and capital stock on the efficient unit of labour ($\hat{K}$). the efficient unit of labour is defined as labour stock augmented by human capital according to the Mincerian methodology of human capital by Barro and Lee (1993). Figure 6.4 represent efficient technology frontier envelopment progress or regress representing years 1970 (blue elements), 1990 (red elements), and 2010 (black elements).

We follow economic development in 2 ways. Firstly, the economic capacity grows. The technological frontier extends to the upper right corner, which indicates increasing input and output per efficient unit of labour. Secondly, we follow the shift of the efficient frontier. Comparing the years 1970 and 1990, we see a slight implosion of defined technology frontier. Envelopment in 1990 imploded a bit comparing the state in 1970. This feature can be ascribed to enormous growth in the amount of employed human capital in the production process. Compared to Henderson and Russell (2005), we used revised human capital data of the new generation of Penn World Tables for Figure 6.4.

Figure 6.4 Data envelopment on real data from 1970, 1990 and 2010 in model with VRS



Source: Author's calculations based on the methodology of Henderson Russell (2005) and data from Penn World tables 9.2

In the following sections, we introduce the next step of intertemporal analysis represented by non-parametric intertemporal decompositions by Henderson and Russell (2005) and Färe at al. (2018) which provide insights into the movement along the efficient frontier.

6.4 Standard Henderson and Russell intertemporal decomposition

This chapter is dedicated to the analysis of Henderson and Russell (2005), who introduce human capital into a productivity convergence model based on the non-parametric decomposition approach proposed by previous contribution by Kumar and Russell (2002). The basic production function by Kumar and Russell (2002) follows the model proposed by Solow (1956) and assumes inputs of labour (L) and capital stock (K) which produce economic output (Y) in the form of gross domestic product. Based on endogenous growth theories by Lucas (1988) and Romer (1990), Henderson and Russell basically follow Hall and Jones (1999) and Bils and Klenow (2000) to augment labour from the basic Solow model with human capital accumulation. Henderson and Russell decompose labour productivity growth into components attributable to technological change (shifts in the world production frontier), efficiency catch-up (movements toward or away from the frontier), and physical and human capital accumulation (movements along the frontier) (Henderson and Russell, 2005).

6.4.1 *Modification of Henderson and Russell decomposition*

We modify the methodology used by Kumar, Russell (2002) and later by Henderson, Russell (2005) to bring a new insight into the human capital literature by the usage of high- and low- skilled rather than Mincerian human capital augmented labour in DEA decomposition to find the contribution of high-skilled labour to economic productivity. We base the modification on the dataset introduced by Lutz et al. (2008). Henderson and Russell's technology contains four macroeconomic variables: aggregate output and three aggregate inputs in the form of labour, physical capital, and human capital. However, they use 4 variables, their model is based on one input and one output approach. They introduce human capital augmented labour and later divide economic output and capital stock by this new measure of efficient labour. Finally, they use economic output and capital stock per efficient unit of labour to construct one input and one output DEA model. They calculate time-variant contra factual input and output measures by variations in GDP, capital stock, labour and human capital from mixed time periods 1 and 2.

First of our contributions into this stream of literature is in introducing labour skill-mix instead of human capital measured by returns to education and average years of schooling from Barro and Lee (1993). Labour mix is composed of an active age population (between 20 to 64 years) divided into the low- and high- skilled labour. Low-skilled labour is represented by no or primary educated population and high-skilled labour by secondary and tertiary educated. Our production function is defined by one output in the form of real gross domestic product (Y) and 3 inputs: low-skilled labour (L^{low}), high-skilled labour (L^{high}), and capital stock (K) all divided by the measure of labour. Let define $\langle Y_{jt}, K_{jt}, L_{jt}^{high}, L_{jt}^{low} \rangle$ where $t = 1, \dots, T$ is period and $j = 1, \dots, J$ denotes country id.

Our second contribution to the Henderson and Russell analysis is a modification of their one input and one output decomposition. Our DEA model for decomposition contains multiple inputs and one output for the technology composed of low- and high- skilled labour mix.

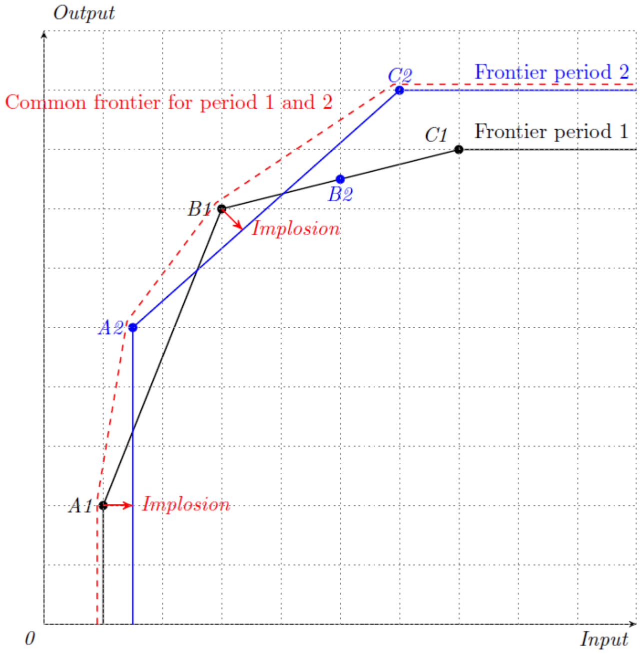
The Farrell (output-based) efficiency index for country j at time t is defined by:

$$E\left(Y_{jt}, K_{jt}, L_{jt}^{high}, L_{jt}^{low}\right) = min\left\{\lambda | \langle \frac{Y_{jt}}{\lambda}, K_{jt}, L_{jt}^{high}, L_{jt}^{low} \rangle \in T_t\right\} \tag{6.34}$$

This index score is the inverse of the maximal proportional amount that output Y_{jt} that can be expanded while remaining technologically feasible. Using the terminology from the previous chapter, we use the DEA model with output orientation. Given the technology T_t and the input quantities $L_{jt}^{high}, L_{jt}^{low}$, and K_{jt}, it is less than or equal to 1. The ratio takes the value of 1 if the jt observation is on the period-t production frontier. In this case, the index is simply the ratio of actual to potential output evaluated at the actual input quantities. In our multiple-output technology, the index is a radial measure of the distance of the actual output vector from the production frontier (Henderson and Russell, 2005).

As well as Henderson and Russell (2005), we use the "sequential production set" to preclude implosion of the frontier over time. Basically, we construct the period-t technology using all data up to that point in time. In particular, we construct a period-t technology frontier using all data up to that point in time. We explain this methodological feature on Figure 6.5.

Figure 6.5 Technology frontier implosion explained on DEA model with VRS



Source: Author's modification of Henderson and Russell (2018) methodology

We recognize the implosion of efficient envelopment between periods 1 and 2 in case of point A1 and B1. If we would measure the efficiency of these points relative to the frontier of only period 2, we would realize, that the frontier has imploded intertemporally. That is why we use for the second-period envelopment common technology frontier composed of data from periods 1 and 2.

We analyse the effects of 5 components of quintipartite decomposition. We find that the contribution of (1) change in efficiency, (2) technological change, (3) capital accumulation (4) low-skilled labour change and 5) high-skilled labour on economic productivity. Letting t and t+1 stand for the base period and the current period, respectively. The potential (production frontier) outputs in the two periods is given by $\bar{y}_t\left(K_t L_t^{high} L_t^{low}\right) = Y_t/e_t$ and $\bar{y}_{t+1}\left(K_{t+1} L_{t+1}^{high} L_{t+1}^{low}\right) = Y_{t+1}/e_{t+1}$, where e_t and e_{t+1} are the values of the efficiency indices in the respective period. Thus:

$$\frac{Y_{t+1}}{Y_t} = \frac{e_{t+1}}{e_t} \frac{\bar{y}_{t+1}\left(K_{t+1} L_{t+1}^{high} L_{t+1}^{low}\right)}{\bar{y}_t\left(K_t L_t^{high} L_t^{low}\right)} \qquad (6.35)$$

Denote $\bar{y}_t\left(K_{t+1} L_{t+1}^{high} L_{t+1}^{low}\right)$ as the potential output at the period $t+1$ capital and labour inputs using the period t technology. Similarly, potential output at the period t capital and labour inputs using the period $t+1$ technology is denoted as $\bar{y}_{t+1}(K_t L_t^{high} L_t^{low})$. Now, let define other combinations. The formula $\bar{y}_t\left(K_t L_t^{high} L_{t+1}^{low}\right)$ denotes the potential output while keeping K and L^{high} from period t, and L^{low} from period $t+1$ using the period t for technology frontier. The formula $\bar{y}_t\left(K_t L_t^{high} L_{t+1}^{low}\right)$ represents the counterfactual to $\bar{y}_t\left(K_{t+1} L_t^{high} L_{t+1}^{low}\right)$ if we would like to check the contribution of capital stock while keeping other components constant (technology and all types of labour). There exist more counterfactual equivalents for the expression (6.36). Multiplying the (6.35) by $\frac{\bar{y}_t(K_{t+1} L_{t+1}^{high} L_{t+1}^{low})}{\bar{y}_t(K_{t+1} L_{t+1}^{high} L_{t+1}^{low})}, \frac{\bar{y}_t(K_t L_{t+1}^{high} L_{t+1}^{low})}{\bar{y}_t(K_t L_{t+1}^{high} L_{t+1}^{low})}, \frac{\bar{y}_t(K_t L_t^{high} L_{t+1}^{low})}{\bar{y}_t(K_t L_t^{high} L_{t+1}^{low})}\ and\ \frac{\bar{y}_t(K_t L_{t+1}^{high} L_t^{low})}{\bar{y}_t(K_t L_{t+1}^{high} L_t^{low})}$, what is the same as multiplying (6.27) by unity, we get:

$$\frac{Y_{t+1}}{Y_t} = \frac{e_{t+1}}{e_t} \times \frac{\bar{y}_{t+1}(K_{t+1}L_{t+1}^{high}L_{t+1}^{low})}{\bar{y}_t(K_{t+1}L_{t+1}^{high}L_{t+1}^{low})} \times \frac{\bar{y}_t(K_{t+1}L_{t+1}^{high}L_{t+1}^{low})}{\bar{y}_t(K_tL_{t+1}^{high}L_{t+1}^{low})} \times \frac{\bar{y}_t(K_tL_{t+1}^{high}L_{t+1}^{low})}{\bar{y}_t(K_tL_t^{high}L_{t+1}^{low})} \times \frac{\bar{y}_t(K_tL_t^{high}L_{t+1}^{low})}{\bar{y}_t(K_tL_t^{high}L_t^{low})} = (TE) \times (TC) \times (KC) \times \left(L^{high}C\right) \times (L^{low}C) \quad (6.36)$$

Following the previous step, we find $q = 12$ equivalent decompositions as in (6.36). Accordingly, the true value of technical efficiency change (TE), technological change (TC), capital stock change(KC), high-skilled $\left(L^{high}C\right)$, and low-skilled labour change $(L^{low}C)$ can be derived as the geometric average of all possible alternatives (Henderson and Russell, 2005).

$$\frac{Y_{t+1}}{Y_t} = \left(\prod_1^q TE\right)^{\frac{1}{q}} \times \left(\prod_1^q TC\right)^{\frac{1}{q}} \times \left(\prod_1^q KC\right)^{\frac{1}{q}} \times \left(\prod_1^q L^{high}C\right)^{\frac{1}{q}} \times \left(\prod_1^q L^{low}C\right)^{\frac{1}{q}} \quad (6.37)$$

We apply the intertemporal decomposition method to reveal the contribution of high-skilled labour on productivity growth. We verify findings from parametric literature, which claims that high-skilled population contributes significantly more to the economic growth than low-skilled (Flabbi and Gatti, 2018). This approach can be further extended also on a more detailed classification of education. At least, Lutz et al. (2008) database provides 8 ISCED qualification level data for a balanced panel of countries back to 1970. Additionally, we keep the analysis simple for later incorporation of the Gini index in Färe et al. (2018) approach introduced in the following chapter.

6.5 Intertemporal decomposition by Färe et al.

Nonparametric decomposition by Färe et al. (2018) introduces the methodology designed to find out how (1) efficiency change, (2) frontier shift, (3) input, and (4) output mix contribute to the change in one of the selected inputs. We focus our analysis on the input of high-skilled labour, or more concretely into the contribution of increasing inequality (the Gini index) on the accumulation of high-skilled labour following the literature of inequality of opportunities and theory of Galor and Zeira (1993).

6.5.1 *Modification of Färe et al. decomposition*

Färe et al. (2018) used a nonparametric decomposition approach to analyse the effects of environmental regulations on employment changes. The modification of their decomposition can be used to quantify the intertemporal change in any selected input due to changes in technical efficiency (TE), technical change (TC), output mix change (OC) and change in the mix of other inputs (IC). The analysis is based on the same contra factual method as in the Henderson and Russell approach. Moreover, we also prohibit the implosion of the technological frontier. In the modified model we extend the number of contributors to introduce the Gini index inequality as a bad output in our technology model. Following the original analysis by Färe et al. (2018), We treat inequality as a bad output with zero jointness with good output. A higher value of bad output translates to the lower value of efficiency score and producing good output does not require producing also bad output so that reducing bad output does not need to be accompanied by a reduction in good output. Another difference to the previous Henderson and Russell model technology is input orientation. As far as we focus on the change in high-skilled labour as an input, it is more comprehensive to use input orientation as in Färe et al. (2018). In aim to keep our formulations simple, we use for input mix K and L^{low} a common notation of X. So that the Farrell (input-based) efficiency index for country j at time t is defined as:

$$E\left(Y_{jt}, Gini_{jt}, L_{jt}^{high}, X_{jt}\right) = max\left\{\lambda | \langle Y_{jt}, Gini_{jt}, \frac{L_{jt}^{high}}{\lambda}, \frac{X_{jt}}{\lambda}\rangle \in T_t\right\} \tag{6.38}$$

where $T = \left\{\left(Y_{jt}, Gini_{jt}, L_{jt}^{high}, X_{jt}\right) : \left(Y_{jt}, Gini_{jt}\right) \in P\left(L_{jt}^{high}, X_{jt}\right)\right\}$, and λ represents the maximum feasible contraction of all inputs. Hence, $E\left(Y_{jt}, Gini_{jt}, L_{jt}^{high}, X_{jt}\right)$, the reciprocal of the Farrell efficiency measure, allows us to solve for the ratio of a DMU's observed level of high-skilled labour relative to its efficient level. It follows that $E\left(Y_{jt}, Gini_{jt}, L_{jt}^{high}, X_{jt}\right) \geq 1$ where a value of unity indicates an observation is efficient and a value exceeding unity indicates inefficiency. As a result, L_{jt}^{high}/λ is the amount of high-skilled labour the country would employ if it were efficient given its observed good output production and bad output production (Färe et al., 2018).

The input-oriented DEA model identifies the technical inefficiency of a country by measuring its maximum potential contraction of all inputs while maintaining its observed production of good and bad outputs. $E_t\left(Y_t, Gini_t, L_t^{high}, X_t\right)$ represents the efficiency of DMU with inputs and outputs from period t compared to the setting of technology from the same period t. In this sense, $E_{t+1}\left(Y_t, Gini_t, L_{t+1}^{high}, X_t\right)$ would represent the efficiency of DMU with inputs and outputs from period t but with the level of skilled labour from period $t+1$ compared to the setting of technology from the same period $t+1$.Contra factual works in the same manner as in the methodology from Henderson and Russell (2005). Mechanism of decomposition is then formulated as (6.39):

$$
\begin{aligned}
\Delta L_t^{high} = \left[\frac{L_{t+1}^{high}}{L_t^{high}}\right] \\
&= \left[\frac{E_{t+1}\left(Y_{t+1}, Gini_{t+1}, L_{t+1}^{high}, X_{t+1}\right)}{E_t\left(Y_t, Gini_t, L_t^{high}, X_t\right)}\right] \times \left[\frac{E_t\left(Y_t, Gini_t, L_t^{high}, X_t\right)}{E_{t+1}\left(Y_t, Gini_t, L_t^{high}, X_t\right)}\right] \\
&\times \left[\frac{E_{t+1}\left(Y_t, Gini_t, L_t^{high}, X_t\right)}{E_{t+1}\left(Y_{t+1}, Gini_t, L_t^{high}, X_t\right)}\right] \times \left[\frac{E_{t+1}\left(Y_{t+1}, Gini_t, L_t^{high}, X_t\right)}{E_{t+1}\left(Y_{t+1}, Gini_{t+1}, L_t^{high}, X_t\right)}\right] \quad (6.39) \\
&\times \left[\frac{L_{t+1}^{high} \Big/ E_{t+1}\left(Y_{t+1}, Gini_{t+1}, L_{t+1}^{high}, X_{t+1}\right)}{L_t^{high} \Big/ E_{t+1}\left(Y_{t+1}, Gini_{t+1}, L_t^{high}, X_t\right)}\right] \\
&= (TE) \times (TC) \times (YC) \times (GiniC) \times (IC)
\end{aligned}
$$

We need to take into consideration also an alternative derivation of decomposition settings in (6.39). If we extend the basic model in E_t technology time dimension instead of E_{t+1} we would derive contra factual situations from (6.39) within E_t technology setting. So that, both alternative decompositions are then averaged by geometrical mean as in the (6.40).

$$
\Delta L_t^{t+1} = \left[\frac{L_{t+1}}{L_t}\right] = \left(\prod_1^2 TE\right)^{\frac{1}{2}} \times \left(\prod_1^2 TC\right)^{\frac{1}{2}} \times \left(\prod_1^2 OC\right)^{\frac{1}{2}} \times \left(\prod_1^2 IC\right)^{\frac{1}{2}} \qquad (6.40)
$$

The idea behind this type of decomposition is described well on Figure 6.6 with geometrical formulation on equitation (6.41) and (6.2). We follow the visualization practice from Färe et al. (2018).

$$\frac{0E}{0A} = \left[\frac{0E/_{0F}}{0A/_{0B}}\right] \times \left[\frac{0A/_{0B}}{0A/_{0J}}\right] \times \left[\frac{0E/_{0K}}{0E/_{0F}}\right] \times \left[\frac{0E/\left(0E/_{0K}\right)}{0A/\left(0A/_{0J}\right)}\right] \tag{6.41}$$

$$= (TE) \times (TC) \times (OC) \times (IC)$$

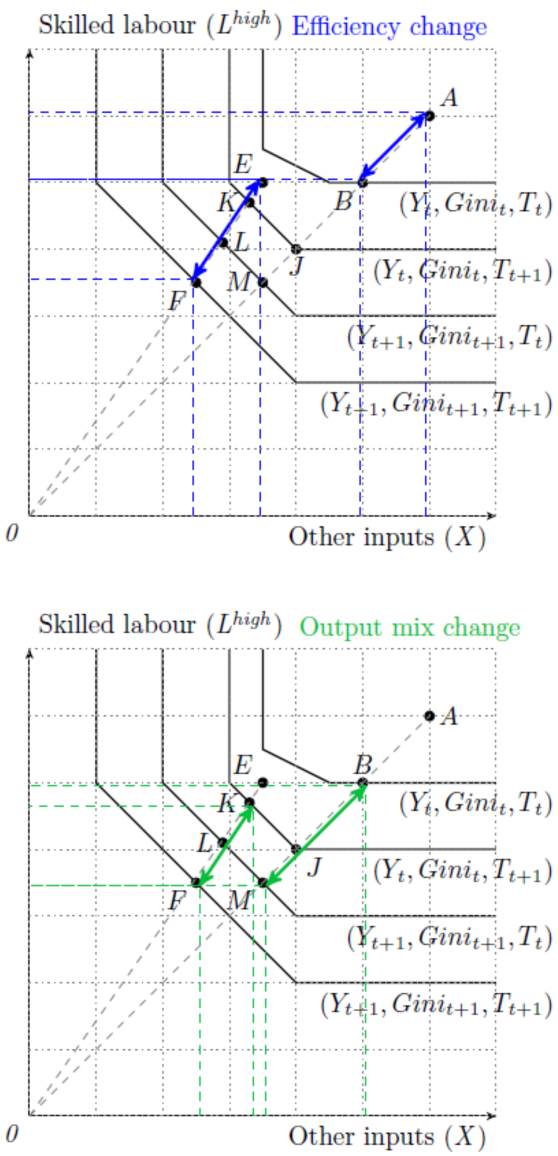
$$\frac{0E}{0A} = \left[\frac{0E/_{0F}}{0A/_{0B}}\right] \times \left[\frac{0E/_{0L}}{0A/_{0F}}\right] \times \left[\frac{0A/_{0B}}{0A/_{0M}}\right] \times \left[\frac{0E/\left(0E/_{0L}\right)}{0A/\left(0A/_{0M}\right)}\right] \tag{6.42}$$

$$= (TE) \times (TC) \times (OC) \times (IC)$$

Figure 6.6 provides 4 isoquants. Isoquant $(Y_t, Gini_t, T_t)$ corresponds to good and bad outputs from period t as well as technology T from period t. Later isoquant $(Y_{t+1}, Gini_{t+1}, T_t)$ corresponds to good and bad outputs from period $t+1$ and technology T from period t. Accordingly, we derive the definition of isoquants $(Y_t, Gini_t, T_{t+1})$ and $(Y_{t+1}, Gini_{t+1}, T_{t+1})$.

TE represents the shift in the employment of high-skilled labour due to the change in technical efficiency. In the graphical meaning it reflects whether observation moved closer to or further from the best-practice isoquant between t and $t+1$ period. Improved technical efficiency ($TE < 1$) decreases employment, while decreased technical efficiency ($TE > 1$) increases employment. The contribution of shift in the efficient frontier to the change in high-skilled labour between 2 periods is named TC as technology change. Technical progress ($TC < 1$) decreases employment while technical regress ($TC > 1$) increases high skills. Accordingly, $YC, GiniC$ describe the change in high-skilled labour attributable to the output mix composed of change in economic output and inequality. IC follows the contribution of input mix to the change in the stock of high-skilled labour in the economy. Likewise, for IC, YC, and $GiniC$ a value exceeding unity indicates the component is associated with increasing ΔL^{high} between period t and period t + 1, while a value less than unity signifies the component is associated with declining ΔL^{high}. Finally, a value of unity indicates the component is associated with no change in ΔL^{high} (Färe et al., 2018).

Figure 6.6 Intertemporal decomposition



Source: Author's modification of Färe et al. (2018)

Modification of Henderson and Russell (2005) and Färe et al. (2018) methodology allows us to contribute into the existing literature on the interrelationship between inequalities, human capital, and economic growth. The first type of decomposition will reveal how does human capital accumulation in the form of the stock of high-skilled labour contribute to the growth of productivity. And the second approach decomposition describes the contribution of income inequalities to the accumulation of high-skilled labour. The following Chapter 7 is dedicated to the description of the dataset of panel data between 1970 and 2010 for both decompositions and in the second section of the following chapter, we present our empirical findings.

7 Empirical analysis

Following the aim of this dissertation thesis, firstly, we use modified intertemporal decomposition by Färe et al. (2018) to reveal the contribution of inequality on the accumulation of high skills in economy. Secondly, we use modified Henderson and Russell (2005) decomposition to find the contribution of high-skilled labour to productivity growth.

In this Chapter 7, we gradually introduce balanced panel data in Section 7.1. We cope with the typical trade-off between covering long enough time period and wide enough sample of countries to bring representative panel data for our decomposition in later Section 7.2. Then, we present empirical results from 3 different panels for Henderson and Russel like decomposition (later on HR) and Färe et al. like decomposition (later on FR).

7.1 Database

This section provides 3 equivalent panel data sets for two time periods covering 40 years of world countries development. We focus on two time periods. First one is between 1970 and 1990 and the second one covers period between 1990 and 2010. The reason for more equivalents of panel data sets is caused by the limited availability of data for inequality measure in historical statistics.

Our decomposition analysis is based on technology for FR decomposition as defined in Section 6.5 and HR decomposition already defined in Section 6.4. Both intertemporal decompositions together require 6 types of variables from 3 different databases. DEA decomposition analysis requires balanced panel. Our technology requires two outputs. First output is the standard measure of real gross domestic product in constant prices (GDP). The second output, which is in the form of bad output, is the Gini index ($Gini$) as standard inequality measure. Capital stock in constant prices (K), low-skilled (L^{low}) and high-skilled labour (L^{high}) represent 3 inputs. We focus on change in inputs and outputs between 3 points in time. Our cross-sections are years 1970, 1990 and 2010. More consistent sample of countries is available for the time period between 1990 and 2010. We provide an analysis of 79 countries for HR and FR decomposition for this period. For the same period is available also extended panel with 161 countries, but only for HR decomposition. Both types of decomposition are analysed also for the complete time span of 1970, 1990 and 2010 thanks to a reduced sample of 33 countries, unfortunately, overrepresented by developed (OECD) countries. In the following sections, we present construction and sources of variables and explain their modification for the following use in alternative labour scenarios. We alternatively use high-skilled and low-skilled labour shares on active population and its employment adjusted measure to partially check whether we get robust results.

It is important to highlight that descriptive statistics in the following subsections represent all data available in source databases. Because we use 3 equivalent panel datasets, we would like to avoid confusion by multiple descriptive statistics.

7.1.1 Economic output and stock of physical capital

Firstly, we use real gross domestic product in constant prices as a standard measure of economic output. We use Penn World Tables (Feenstra et al., 2015) (later on PWT) as a standardized source of historical data. The constant prices ensure that we capture the intertemporal aspect of our analysis. PWT in this purpose provide a measure of real GDP at constant 2011 national prices in millions of USD. The same approach as for GDP we applied for capital stock (K) data. PWT define capital stock at constant 2011 national prices in millions of USD.

Table 7.1 Statistics about Available Gross Domestic Product and Capital Stock

	1970		1990		2010	
	GDP	K	GDP	K	GDP	K
Obs.	156	156	180	180	182	180
Min.	7.87	15.69	59.66	163.02	86.47	1,687.98
Max.	4,858,091.50	17,994,764.00	9,189,259.00	32,134,608.00	15,305,223.00	51,328,388.00
S.d.	449,775.26	1,638,917.21	852,238.13	3,145,337.13	1,634,773.99	5,959,836.59
Mean	134,891.51	447,449.98	267,505.05	1,022,012.04	502,643.45	1,926,282.10
Med.	14,679.56	37,257.14	31,587.24	96,999.91	55,642.20	195,941.75

* Data are in millions

Source: Feenstra et al., 2015

We are aware about probably better estimation of capital stock historical data by Berlemann et al. (2017), but we keep PWT as a source for capital stock to prevent any issue with the harmonization of two different datasets. Both GDP and capital stock are described in the Table 7.1. The latest Penn World Tables generation 9.1. covers 182 countries between 1950 and 2017 (Feenstra et al., 2015).

7.1.2 Low- and high-skilled labour

Human capital databases usually cover a wide range of world countries for recent years. Unfortunately, to get long enough time span back in decades use to be an issue for many less developed countries. Standard databases usually provide information about mean years of schooling or enrolment rates. These variables are used in broad literature about human capital based on the Mincerian measure of returns to education (Hall and Jones, 1999). This measure already used Henderson and Russel (2005) in their nonparametric decomposition. But to measure how many individuals in a country possess a specific level of education was not possible for many countries. Since the International Institute for Applied Systems Analysis (IIASA) and the Vienna Institute of Demography (VID) published their dataset based on the demographic method of multistate back-projection (later on as VID-IIASA). This dataset provides a full reconstruction of educational attainment levels by age and sex for 210 countries and territories back to 1970. Lutz et al. (2018) provide also projections for the 21st century. This unique dataset provides new possibilities to analyse human capital and the consequences of its accumulation. The education levels in combination with demographical dimension have already been analysed in Cuaresma and Lutz (2007).

VID-IIASA database provides a detailed matrix of data with dimensions of the completed level of education, age structure, sex and time dimension. For our analysis, it is sufficient to follow the education level in time. We follow mainly productivity literature which use variables adjusted per worker, that is why we focus on population aged between 16 and 64. We assume that the population in active age can be treated as our input or labour capacity in the economy. We use in further analysis only simple differentiation of active population on low-skilled labour L^{low} and high-skilled labour L^{high}. Although, there is a possibility to extend decomposition and introduce more skill levels or incorporate age structure to the nonparametric decomposition. For example, we could easily extend the technology on $L^{low\times young}$, $L^{high\times young}$, $L^{low\times old}$ and $L^{high\times old}$. VID-IIASA provides education levels based on ISCED classification. We understand classes of "no education, incomplete primary and primary" education as L^{low} and "lower secondary, upper secondary and post-secondary" education as L^{high}. As we already mentioned we focus on 3 cross-sections covering 4 decades (1970, 1990 and 2010). As we showed in Section 2.2.1, this period is typical for increasing inequalities within the developed countries. In later steps, we modify L^{low} and L^{high} for employment rates available in Penn World Tables. We use this adjusted measure of labour not only to avoid methodological challenge when the sum of skill groups shares without employment adjustment is equal to one[4].

Table 7.2 Statistics about education levels (share on active population)

	1970		1990		2010	
	L_{low}	L_{high}	L_{low}	L_{high}	L_{low}	L_{high}
Obs.	163	163	163	163	163	163
Min.	0.0029	0.0001	0.0057	0.0077	0.0056	0.0413
Max.	0.9999	0.9971	0.9923	0.9943	0.9587	0.9944
S.d.	0.2763	0.2763	0.3027	0.3027	0.2898	0.2898
Mean	0.6934	0.3066	0.5179	0.4821	0.3765	0.6235
Med.	0.7715	0.2285	0.5555	0.4445	0.3526	0.6474

Source: Lutz, Goujon, KC, Stonawski, and Stilianakis (2018)

We adjust the population aged between 15 and 64 years by employment rates for each specific country and time period. We do it to capture labour inputs used in economic production process better. For this adjustment, we need to assume that the same employment rate holds for both labour-skill groups. We admit that this assumption can partially influence our results, what we explain in the next parts. For this purpose, we combine data from PWT and VID-IIASA. While POP and EMP represent the size of population and employment rate, indexes PWT and $VID - IIASA$ denote source databases. We formalize the calculation of employment adjusted low- and high- skilled labour as follows:

$$L^*_{low/high} = \frac{L_{low/high}}{L_{VID-IIASA}} \times \frac{POP_{VID-IIASA}}{POP_{PWT}} \times EMP_{PWT} \tag{7.1}$$

$L^*_{low/high}$ represents employed population in active age with low and high skills.

To assume the same employment rate and labour participation for both of labour skill groups may be counter-intuitive and misleading in the next empirical section. Unfortunately, ideal data are not available, so that we would like to introduce at least the present state of labour variables among heterogeneous countries and to provide some findings from recent literature. Loichinger and Prskawetz (2017) introduce well the main demographic characteristics of labour force participation rates changes between 2000 and 2010 in selected European countries by age and education. One among other interesting statistics provides an excellent example of this labour demographic interrelations. They provide a piece of

[4] We have run all models also on the equivalent data without employment adjustment without significant differences in results.

evidence, that the increase in participation among older people is mainly explained by participation increases among those with non-tertiary education and that it is reinforced by a general shift toward higher levels of educational attainment in higher age cohorts. Later, OECD (2013) study shows that employment rates are highest for people with tertiary education, whereas their unemployment rates are consistently lower than for those with less educational attainment. We provide a more heterogeneous sample of countries and compare OECD countries, LDCs and Other countries.

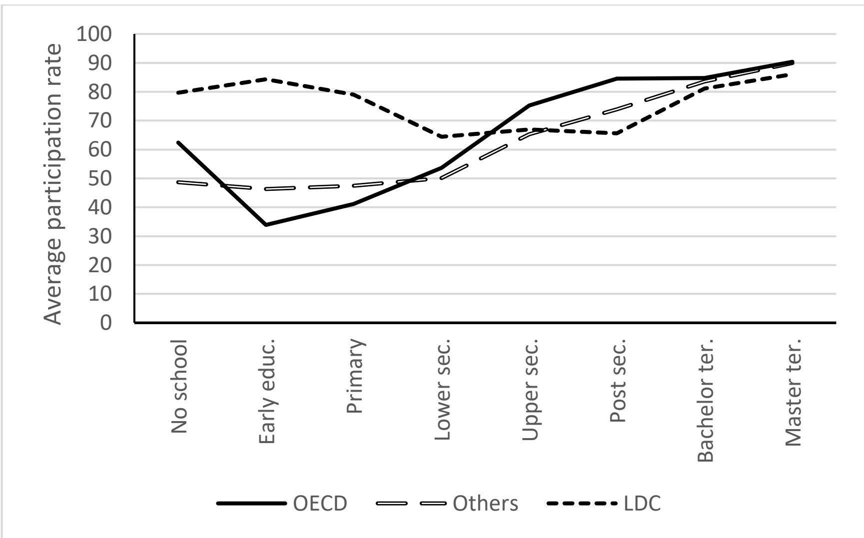
Table 7.3 Labour participation and unemployment rate in 2015

		No. school	Early educ.	Primary	Lover sec.	Upper sec.	Post sec.	Bachelor ter.	Master ter.
Participation rate	OECD	14	22	33	34	34	26	34	34
	Others	13	17	20	21	21	14	19	16
	LDC	6	6	8	8	8	6	8	6
Unemployment rate	OECD	10	16	31	34	34	25	34	34
	Others	9	14	19	19	21	12	16	12
	LDC	3	2	3	4	4	2	2	1

Source: ILOSTAT (2020)

Table 7.3 summarizes a sample of countries in each development group with available data for labour participation and unemployment rate statistics from ILOSTAT (2020) for the most recent and the most complete year 2015. Unfortunately, LDC sample is strongly overrepresented by data from only 3 countries Bhutan, Mozambique and Senegal.

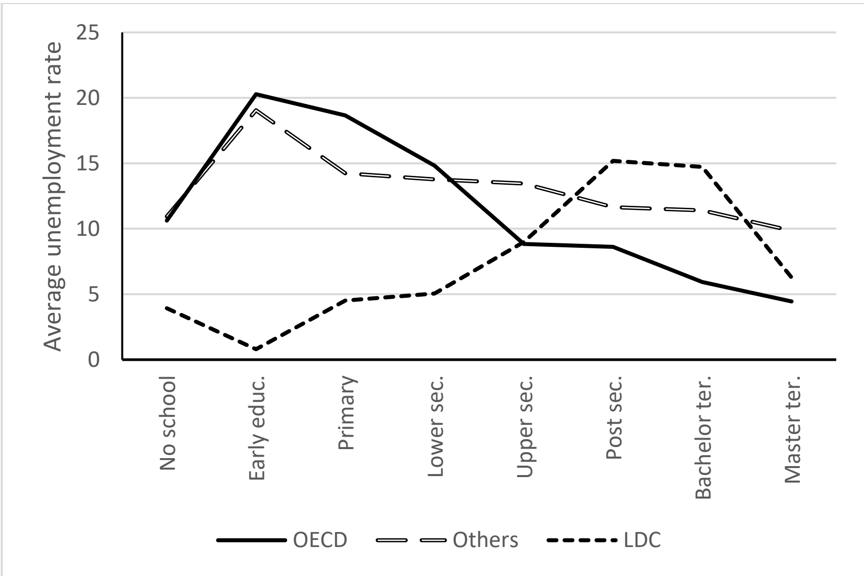
Figure 7.1 Labour participation rate in development groups according to level of education



Source: Author's modification based on ILOSTAT (2020)

On Figure 7.1, we can easily recognize the rising labour participation rate with increasing level of education in case of OECD and other countries. The situation is quite different in the case of LDCs. LDCs exhibit ambiguous relation. This can be probably caused by underdeveloped educational system, weak labour market or limited sample of countries. Next Figure 7.2 provides statistics about the unemployment rate among development groups. In this case, LDCs again provides a counter-intuitive relation. While OECD and other countries exhibit expected decreasing unemployment rate with increasing education, in case of LDCs the relation is reversed.

Figure 7.2 Unemployment rate in development groups according to level of education



Source: Author's modification based on ILOSTAT (2020)

Anyway, this part is dedicated to the simple notion, how imprecise the assumption about similar employment rate for high-skilled and low-skilled labour could be. As Loichinger and Prskawetz (2017) explains, this trend changes over time, so that it is not possible to get reliable historical data. We can only summarize that the expected relationship is stronger in the case of OECD than other countries in case of participation and unemployment rate and that the limited sample of LDCs provides very suspicious statistics.

7.1.3 The Gini Index as a standard measure of inequality

As we already summarized in Section 2.2, there are several alternative measures of inequality. From top quantile share through different types of indexes covering whole distribution to absolute or relative poverty rates. Unfortunately, criteria about coverage for

40 years and significant panel of countries accomplishes only the general measure of the Gini index. The Standardized World Income Inequality Database Version 8 (Solt, 2019) (later on SWIID) currently provides harmonised Gini indices of disposable and market income inequality for 196 countries since 1960, but the number with the Gini index availability decreases with time. While we use the Gini index just in one of the decompositions with technology determining high skilled labour, we use a measure of disposable income after the government redistribution rather than the Gini index for market incomes. Additionally, we admit that government redistribution uses to be higher in developed countries, but the effect of redistribution is out of the scope of this thesis. Anyway, for the theory about the accumulation of human capital based on the assumption of imperfect capital markets, it is more important to follow disposable household income or rather its wealth. The decision about investments to human capital is derived according to household sources. Indeed, we do not control for costs of education and educational system as a public good. The Table 7.4 summarizes available data about the Gini index.

Table 7.4 Statistics about the Gini Index for Disposable Income

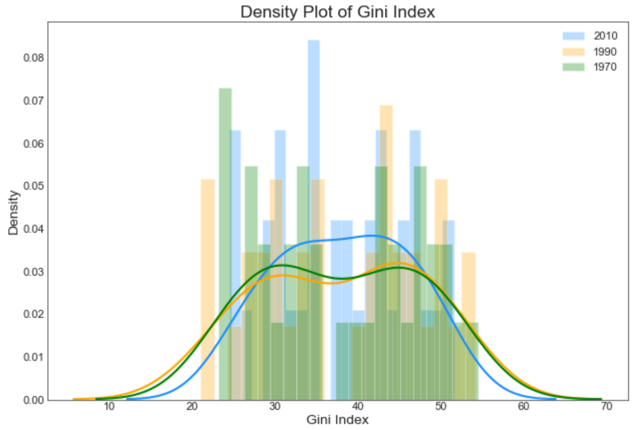
	1970	1990	2010
Obs.	35	103	136
Min.	22.70	18.10	23.80
Max.	54.50	58.50	60.90
S.d.	9.05	9.58	7.93
Mean	37.55	36.99	38.22
Med.	38.10	36.80	38.20

* data for Gini index between 0 and 100

Source: Solt (2019)

Figure 7.3 and Figure 7.4 provide intuitive insight into the distribution of within-country disposable income measured by the Gini index. In the case of Figure 7.3, we compare the distribution of the Gini index for 35 countries for which data are available back to 1970. In particular, it shows the change of inequalities of disposable incomes between 1970, 1990 and 2010. We see that upper and lower tails of the Gini index vanishes in time and it starts to concentrate between values of 30 and 45 in 2010. First two periods describe rather two-peak distribution at values 30 and 45. But Figure 7.3 presents tiny sample which is consistent in the time, but unfortunately it is not representative over world countries.

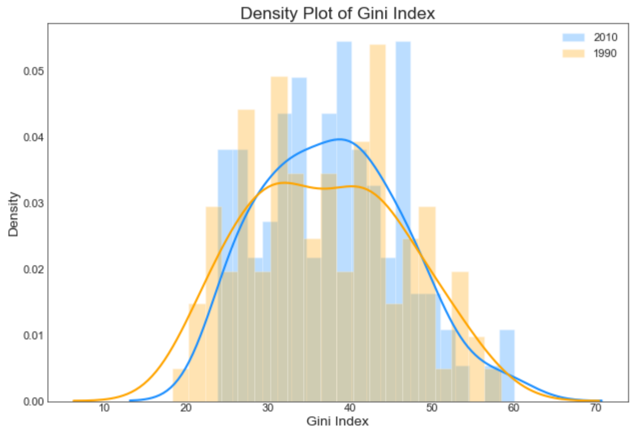
Figure 7.3 Kernel Density of the Gini index for disposable household income between 1970 and 2010 among 35 countries



Source: Author's modification based on Solt (2019)

Figure 7.4 describes distribution of the Gini index of disposable income as well but on a significantly wider set of countries but only for the period between 1990 and 2010. The sample of 101 countries validates findings from previous figure about the concentration of disposable income Gini index around the value of 40, while the distribution in 1990 was flatter with ambiguous peak between 30 and 44. Interesting is also to focus on the left and right tail of its distribution. While it looks that inequalities increased in the most equal countries on the left tail of the distribution (probably post-soviet countries), the blue column around the level of 60 indicates that inequalities slightly increased also on the very top of the distribution.

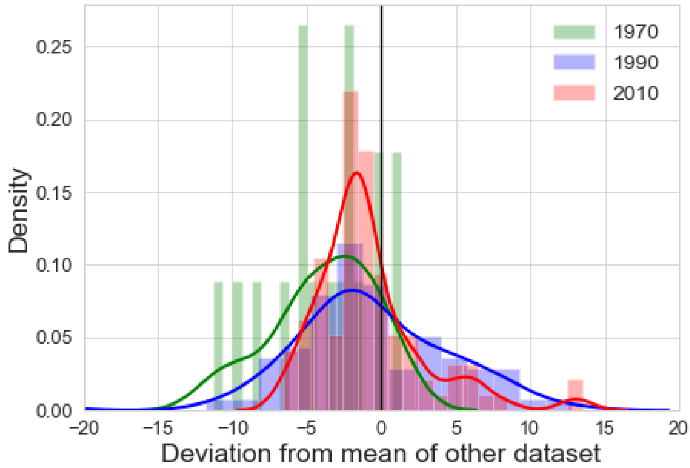
Figure 7.4 Kernel Density of the Gini index for disposable household income among 101 countries between 1990 and 2010



Source: Author's modification based on Solt (2019)

While the Solt (2019) database provides comparable and standardized data about the Gini index for a wide range of countries and time periods, we compare it at least to "All the Ginis " dataset composed by Milanovic (2016) and provided by Stone Center on Socio-Economic Inequality. This dataset consists only of the Gini coefficients that have been calculated from actual household surveys. It uses no Gini estimates produced by regressions or short-cut methods. Database covers 201 countries over period of 1948-2017 with total 2276 country-year Gini indices. This database represents a compilation and adaptation of the Gini coefficients retrieved from nine sources.

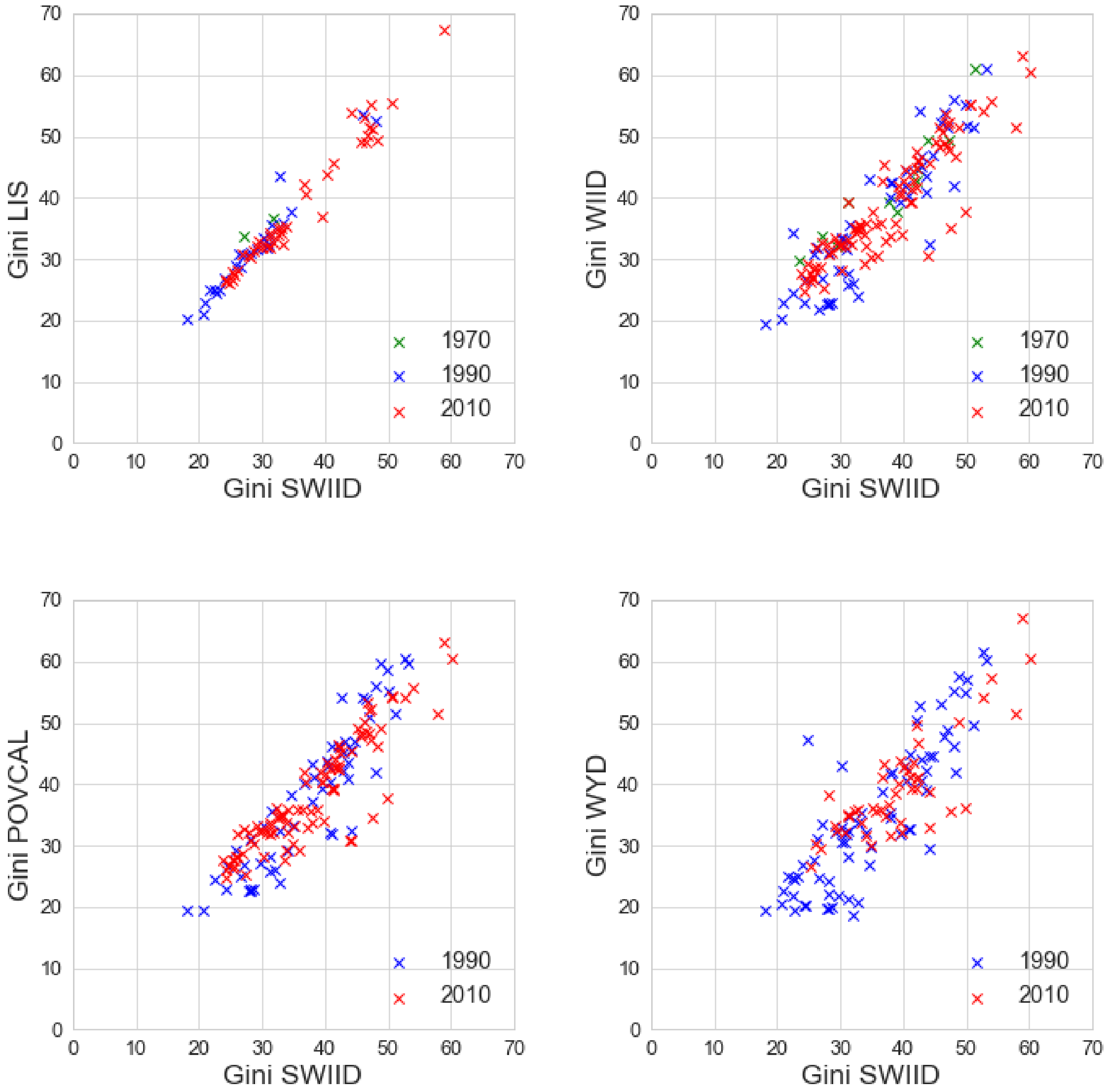
Figure 7.5 Deviation from mean Gini of all other datasets available in country-year



Source: Author's modification based on "All the Ginis" (2019) and Solt (2019)

On Figure 7.6, we compare SWIID with Luxembourg Income Study (LIS) which covers the Gini index of mostly developed countries calculated from direct access to household surveys and microdata. The World Institute for Development Research (WIID) dataset covers 1386 Gini observations compiled from various sources, some of which are based on direct access to household surveys and others to grouped data. POVCAL is World Bank-based dataset of 1711 Gini indices the most of which are calculated from direct access to household surveys. World Income Distribution (WYD) covers 642 Gini observations of which about 90 per cent is calculated from direct access to household surveys (Milanovic, 2019).

Figure 7.6 SWIID Gini indices compared to "All the Ginis" dataset namely LIS, WIID, POVCAL and WYD data sets



Source: Author's modification based on "All the Ginis" (2019) and Solt (2019)

We see on Figure 7.5 that on average SWIID Gini index of disposable income is on average around 2 points lower, than the average of other datasets. This can be caused by differentiation of marketed and disposable income in the case of SWIID. Figure 7.6 provides insight into the consistency of SWIID Gini index with four biggest datasets from "All the Ginis" partial datasets. We see that these partial datasets do not cover 1970 and that the consistency is quite high.

7.1.4 *Normalisation of variables for the model and selection of samples for the non-parametric decomposition*

Later, we normalise the variables listed above by the active population. The reason for normalisation comes from the basic DEA model with constant returns to scale which is later used in decomposition. GDP and capital stock are divided by the active population. The Gini index does not need to be modified while it is already indexed as a relative number between 0 and 1. Regarding the labour, we follow the Section 7.1.2. Accordingly, we get shares of low- and high- skilled employed on the active population. So that the sum of L_{low} and L_{high} is less than unity. Because the equivalent not adjusted by employment gives sum equal 1, it could cause inconveniences in DEA analysis. Moreover, this equivalent does not provide statistically different results, than employment adjusted skill groups, we omit analysis based on this statistic. We present available data described in more detail in Table 7.5.

Table 7.5 Statistics for all Available Data

1970	$GINI$	GDP	K	L_{low}	L_{high}
Obs.	35	139	139	139	139
Min.	0.232	0.6	0.5	0.002	0.004
Max.	0.545	375.9	1566.7	1.004	0.757
S.d.	0.092	49.1	139.9	0.202	0.197
Mean	0.376	20.2	58.2	0.437	0.201
Med.	0.378	7.0	21.6	0.420	0.140

1990	$GINI$	GDP	K	L_{low}	L_{high}
Obs.	101	162	162	162	162
Min.	0.182	0.7	0.8	0.004	0.003
Max.	0.584	120.5	365.7	0.909	0.874
S.d.	0.096	19.4	78.3	0.221	0.232
Mean	0.370	19.1	74.7	0.330	0.317
Med.	0.368	13.1	47.5	0.304	0.244

2010	$GINI$	GDP	K	L_{low}	L_{high}
Obs.	135	163	163	162	162
Min.	0.238	1.2	2.3	0.004	0.037
Max.	0.611	173.1	474.3	0.940	0.869
S.d.	0.083	27.1	106.0	0.211	0.206
Mean	0.384	26.3	101.5	0.246	0.399
Med.	0.381	18.1	62.2	0.211	0.392

**Gini index is from interval 0-1, GDP and K are in thousands and L^*_{low}, L_{low}, L^*_{high} and L_{high} are in labour shares*

Source: Author's modification of Solt (2019), Lutz et al. (2018) and Feenstra et al. (2015)

In the following parts, we discuss the availability of data which is the key determinant for building up a balanced panel data set for the decomposition part. After the modification of variables, the availability for two decomposition approaches or two types of panels is summarized in the Table 7.6

Table 7.6 Availability of Variables

	$GINI$	GDP	K	L_{low}	L_{high}
1970	35	139	139	139	139
1990	101	162	162	162	162
2010	135	163	163	162	162

Source: Author's calculations

Altogether, we have 8 alternative panel datasets for 2 alternative time intervals with different number of covered countries better described in the following Table 7.7. There are different criteria for HR and FR decomposition based on the availability of the Gini index. Therefore, it is also good to later focus on 1970-2010 and 1990-2010 periods separately.

Table 7.7 Statistics about Availability of Data for FR and HR decompositions

Approach to Data	Employment adj.		Active population	
Decomposition	FR	HR	FR	HR
Period 70-90-10	**33**	103	34	139
Period 90-10	**97**	**161**	97	162

Source: Author's calculations

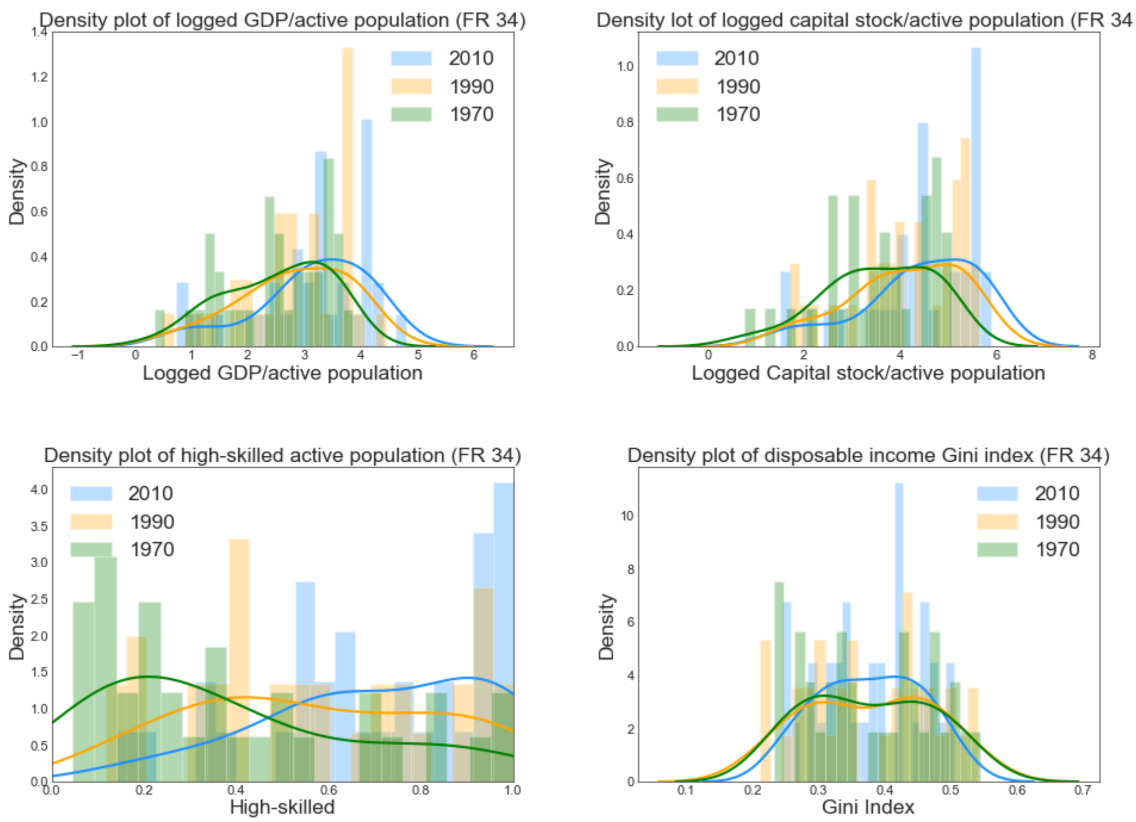
Deciding which panel is feasible for partial decompositions is based on whether the data is available in all of 1970-1990-2010 periods or only in 1990-2010 periods. Information about the Gini index is needed for the FR decomposition what is the second limitation on dataset composition. In particular, the approach based on employment adjusted labour mix provides a panel of 103 countries for HR decomposition and only 33 DMUs for FR decomposition during 1970-1990-2010 period. Doing so, we get the overall analysis of a stable sample among all alternative decompositions for 1970-1990-2010 period.

We provide panel dataset of 97 countries for the reduced time span of period between 1990-2010. This panel contains a wider range of countries. Especially, many countries with communist history are not present in the "33" panel. That is to run FR decomposition and HR decomposition also on reduced time period panel, but with wider and more heterogeneous sample of countries can bring interesting findings.

Bad availability of the Gini index information reduces datasets for single HR decomposition which could be provided by better data coverage. Single HR decomposition can be applied on panel datasets of 103 countries for 1970-1990-2010 period and 161 countries for reduced period of 1990-2010. Another determinant for panel competition is the presence of outliers which can have an unpleasant impact on the effective frontier formation. We discuss this challenge in the following subsections.

We introduce the following figures to better describe the development of variables over time. We focus on the more robust panel of active population labour approach. Variables logged GDP per active age population, logged capital stock on active age individual, the share of high-skilled among active age population and the Gini index are depicted using distributions by the mix of a histogram and simple kernel density. These distributions show us the development of variables through 1970-1990-2010 or 1990-2010 periods depending on the decomposition type and time span.

Figure 7.7 Distribution of variables (Active population, 34 countries, 1970-1990-2010)



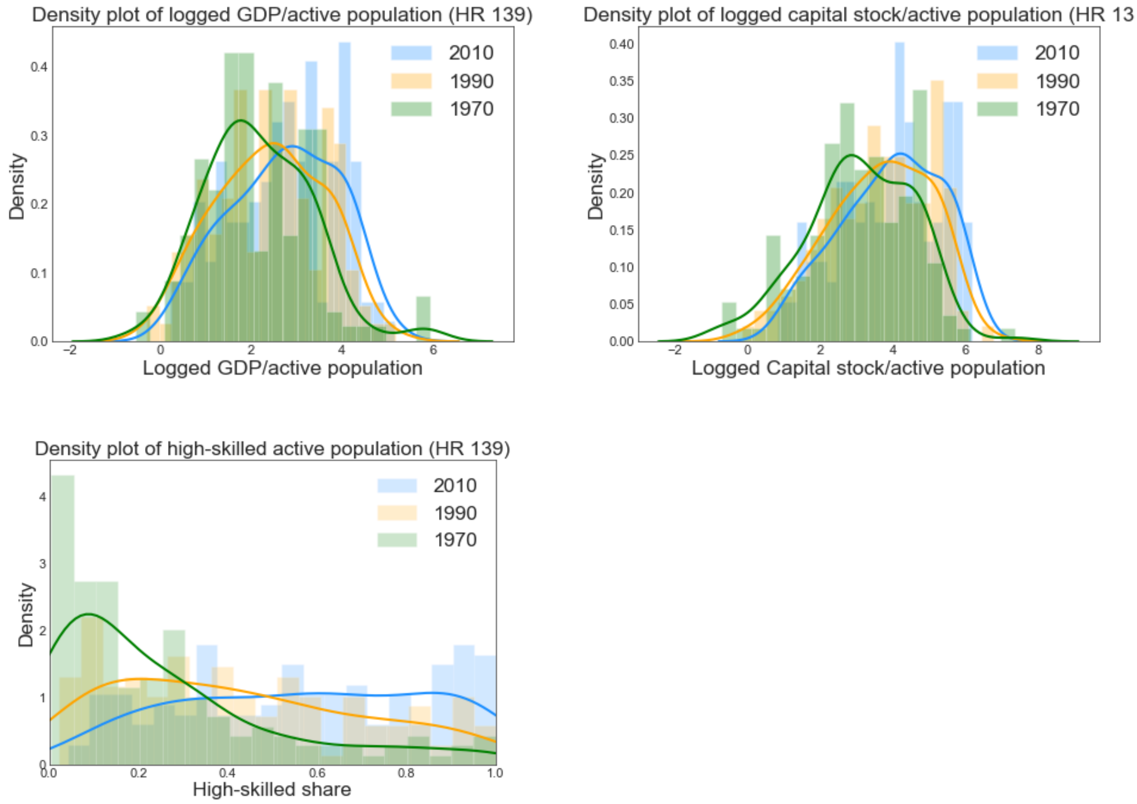
Source: Author's calculations

The first and the second quadrant of Figure 7.7 describes well that logged GDP and capital stock per active population developed similarly over time. This reduced dataset of 34 countries highlights the main contours of variable distribution changes over 1970-1990-2010. There is the two-peak distribution for productivity as well as for an increase in capital per worker since 1970. The distribution changes only in its width, distribution flattens and develops its right tail. Rich countries increases the level of product and capital stock per population, while poor nations try to catch them up. There is a proportion of poor countries which keep the pace of the developed world, but there is still a significant proportion of countries which lack the progress in these measures.

The share of high-skilled labour is described in the third quadrant of Figure 7.7. Period of 1970-1990-2010 captures well the exact time span of rapid increase in high-skilled labour worldwide. Kernel densities for selected time periods clearly show that the proportion of countries where high-skilled labour is a major part of the active population grew dramatically. We can see this transformation because education structure changes by the education of younger age cohorts, which possess better opportunities for education as noticed by Cuaresma and Lutz (2007). While the proportion of countries with more than 90 per cent of the high-skilled population in active age was only 4.29% of 162 countries in 1970, in 2010 this number increased on 26.38% of world countries. For the same time, the median proportion of high-skilled labour among the active population increased from 22.58% to 64.74% and average among countries raised from 30.66% to 62.35%. These statistics are better described on the third quadrant of Figure 7.8 and the education inequality statistics on Figure 3.2.

We validate the main contours of distributions of productivity, capital per capita and high-skilled labour share from previous reduced data also among 139 world countries for time span 1970-1990-2010 on the Figure 7.8 but without unavailable Gini index distribution. On the contrary, this set of countries highlights the different concentration of low values. Naturally, countries in the previous sample were biased by availability of the Gini index, while the Gini index is usually accessible for countries advanced institutions providing national surveys. For this reason, the first sample represented developed economies in higher proportion. However, the flattening two-peak distribution of logged GDP and capital stock per active population is confirmed. Also increasing share and decreasing inequality in high-skilled labour share can be validated.

Figure 7.8 Distribution of variables (Active population, 139 countries, 1970-1990-2010)

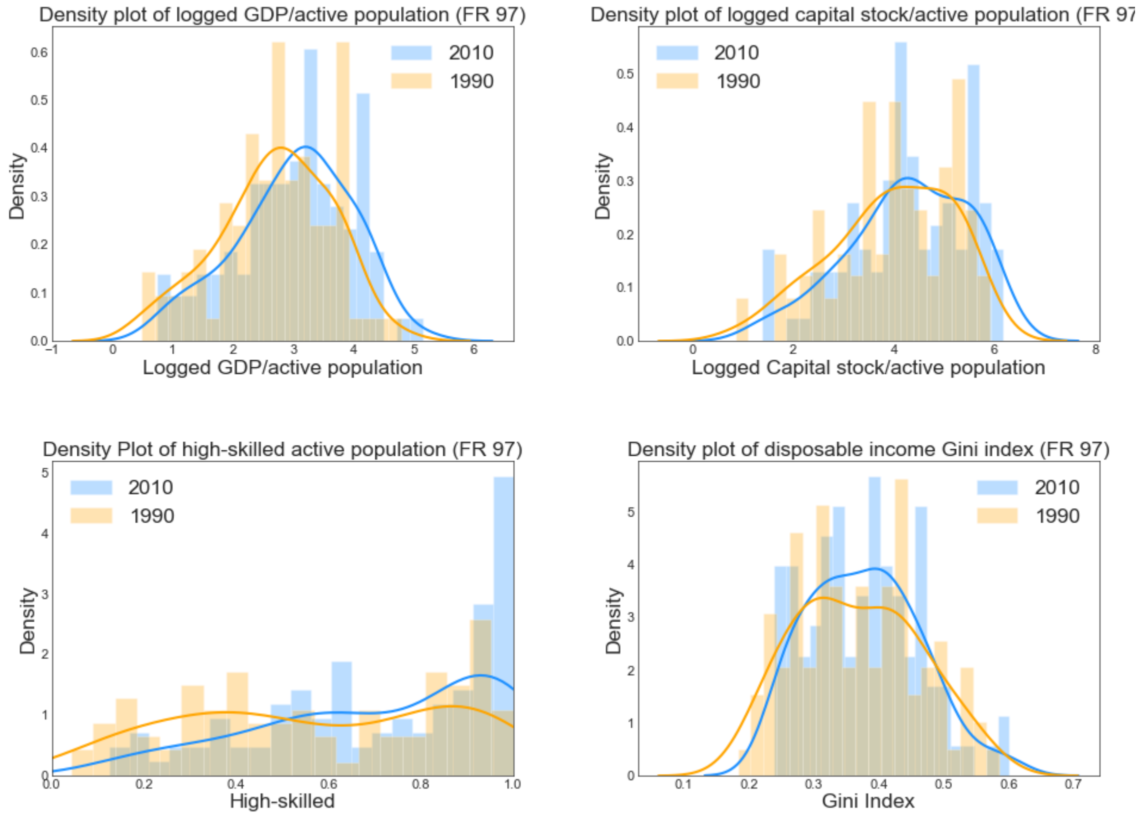


Source: Author's calculations

Figure 7.9 focuses on period of 1990-2010 with dataset of maximum 97 countries feasible for both of decompositions. These 97 countries provide information about many countries which did not exist in 1970 or did not provide feasible data.

Figure 7.9 also confirms the findings from previous datasets. In the following part, we describe the issue of outliers and final decision about panels for further decomposition analysis. In this part, we decide to use 3 datasets for further analysis. The first dataset of only 33 countries will represent the sample for FR and HR decomposition covering all time periods 1970-1990-2010. Later we identify outlier countries and propose a panel sample of 79 DMUs out of 97 for reduced period of 1990-2010. This sample is also available for FR and HR decomposition. We try to get rid of outliers because it could affect efficient frontier and individual efficiency score as was explained in Chapter 5. The last dataset of 161 countries is designed only for the purpose of HR decomposition without the Gini index. It contains all available countries including outlier countries.

Figure 7.9 Distribution of variables (Active population, 97 countries, 1990-2010)



Source: Author's calculations

Literature commonly identifies oil countries as usual outliers. In DEA models, these countries score as efficient DMUs because their extremely high GDP per capita compared to other inputs. The reason is their wealth of natural resources that affects the production technology which acts with a low proportion of labour on the unit of production and so disproportional productivity. For this reason, oil countries could have an unpleasant effect on the frontier composition in simple DEA model as well as in intertemporal analysis. That is why, if the sample width allows so, we avoid countries like United Arab Emirates, Azerbaijan, Kuwait, Norway, Qatar or Saudi Arabia.

Another group of outliers is a specific type of microstates focusing on financial and other services with specific production technology. We identified city countries which could unproportionally reshape technologically efficient envelopment. Belize, Cyprus, Curacao, Hong Kong, Luxembourg, Macao or Singapore were identified as outliers which we aim to avoid. In dataset of 79 countries

Table 7.8 summarizes the composition of available panel datasets. We differentiate advanced, developing and the least developed countries in the next sections for our analysis.

That is why we define their status according to the United Nations [5]definition for Least Developed Countries (LDC) and developed definition comes from OECD membership[6]. We find 39 out of 162 countries with LDC or former LDC status and 36 countries as OECD members.

Table 7.8 Heterogeneity of Available Panel Datasets

Decomposition	FR					HR				
Category	All	Oil ctr.	Micro-states	LDC	Others	All	Oil ctr.	Micro-states	LDC	Others
Period 70-90-10	**<u>33</u>**	1	0	3	29	103	5	4	18	76
Period 90-10	97	3	3	12	**<u>79</u>**	**<u>161</u>**	6	6	39	110

Source: Author's calculations

We decide to focus firstly on the dataset containing 33 countries (16 with OECD status). This sample contains outlier countries (Oil countries and Microstates) or LDCs, in order to keep tiny sample large enough for period of 1970-1990-2010 and both of decomposition types. Secondly, we target on dataset covering 79 countries without outlier countries and LDCs (97 minus 3 oil countries, 3 microstates and 12 LDCs) for FR as well as for HR decomposition during the period of 1990-2010. Finally, we focus on the full dataset of 161 countries (containing oil countries microstates and LDCs) only for HR decomposition in the time span of 1990-2010. Next Section 6.2. presents our findings from HR and FR decompositions applied on panel datasets defined in this subsection.

7.2 Empirical results

In the previous chapters, we introduced and later modified non-parametric decompositions by Färe et al. (2018) and Henderson and Russell (2005). As we already mentioned, we aim to contribute to the discussion about how does increasing inequality contribute to the human capital accumulation in the form of high-skilled labour and consequently how does the high-skilled labour share contribute to the economic productivity.

Regarding the DEA decomposition, we cannot talk about correlation not even about causality between selected variables. Instead, we recognize the shift of world technology frontier and movement towards or away from it. Individual result from decomposition talks about the development of certain DMU or country in multiple input and output dimensions.

[5] https://www.un.org/development/desa/dpad/least-developed-country-category.html
[6] https://www.oecd.org/about/document/list-oecd-member-countries.htm

From the theoretical point of view, we base our analysis on the literature from previous Chapters 2, 3 and 4, which provides arguments for the existence of interrelations between inequality, human capital stock and economic productivity.

In the following chapter, we provide a presentation of our results from 2 equivalent decompositions. Because the decomposition provides a result for each individual country and variable, it is necessary to present results of our decompositions in comprehensive density figures and box plots rather than large tables which are available in Appendix. In Section 7.2.1, we present 2 tables on the sample of 33 countries. In other sections, we use only histograms, kernel density and boxplot figures to compare results from different time periods or development category of countries.

To keep logical order from previous chapters, our concept is firstly to reveal the contribution of inequalities on the accumulation of high-skilled labour among employment adjusted active population with an additional contribution of frontier shift, efficiency change, output change and input mix change. In the second part, we describe the contribution of consequent change in high-skilled labour shares on the productivity change. For the first objective, we incorporate Färe et al. (2018) decomposition (later as FR) To verify findings of parametric literature about unpleasant effects of inequalities on human capital formation especially among developed countries (Galor and Zeira, 1993). And for the second goal is important decomposition proposed by Henderson and Russell (2005) (later as HR) to verify the positive contribution of increasing human capital formation as a prime engine of progress in economic productivity. We present in the following section FR and HR decompositions on 3-panel datasets ("33", "79" and "161") covering the time period between 1970-2010.

7.2.1 Results from the "33" dataset

Dataset "33", the balanced panel of 33 countries, allows us to run both decompositions (FR and HR) for both time periods 1970-1990 and 1990-2010. This dataset describes only a small sample of world countries which is hard to consider as representative for world population. On the first sight, developed economies are overrepresented in this sample. 16 OECD countries in sample is unproportionally too many compared to 3 LDCs and 14 other countries. On the other hand, the "33" dataset is the unique opportunity to understand the whole notion of our analysis of the complete time period. Other 2 datasets in the following sections lose the1970-2010 time period for FR decomposition because of seldom availability of the Gini index data in historical statistics.

Table 7.9 FR "33" 1970-1990 and 1990-2010

	1970 - 1990						1990 - 2010					
(33)	Δ l_high	EFΔ	TCΔ	IMΔ	OMΔ	GiΔ	Δ l_high	EFΔ	TCΔ	IMΔ	OMΔ	GiΔ
Argentina	1.797	1.436	0.999	1.473	0.89	0.955	1.586	0.888	0.891	1.263	1.588	1
Australia	1.299	1.021	0.973	1.037	1.278	0.987	1.16	1.075	0.908	0.81	1.466	1
Bangladesh	1.567	1.622	1	1.039	0.93	1	1.775	1.468	0.868	0.833	1.672	1
Brazil	2.316	1.01	0.998	1.508	1.53	0.996	1.367	1.032	0.899	1.194	1.229	1.005
Canada	1.37	1.01	0.925	1.064	1.36	1.014	1.094	1.143	0.902	0.84	1.265	0.999
Chile	1.526	0.76	1	1.839	1.092	1	1.372	1.041	0.929	0.698	2.022	1.005
Colombia	2.344	0.918	1	1.946	1.311	1	1.695	1.013	0.91	1.449	1.269	1
Costa Rica	1.786	1.276	1	1.213	1.154	1	1.375	1.112	0.914	0.925	1.475	0.992
Germany	0.957	1.025	0.898	0.686	1.515	1	1.061	1.115	0.898	0.775	1.367	1
Finland	1.609	1.093	0.781	1.021	1.782	1.035	1.132	1.105	0.841	0.874	1.4	0.996
France	1.411	1.083	0.735	1.112	1.531	1.041	1.275	1.307	0.757	1.003	1.284	1
United Kingdom	1.012	1	0.709	1.013	1.54	0.915	0.98	1	0.726	1	1.357	0.994
Hungary	1.292	1.019	0.992	0.721	1.818	0.976	0.823	1.219	0.907	0.589	1.265	1
Indonesia	3.326	1.104	1	1.341	2.245	1	1.672	1.283	0.881	0.878	1.712	0.985
Iran	2.554	1.614	0.913	2.544	0.66	1.032	1.452	1.13	0.854	1.283	1.168	1.005
Italy	1.869	1.018	0.749	1.415	1.615	1.073	1.443	1.554	0.757	1.008	1.218	0.999
Japan	1.101	1.191	0.989	0.466	2.01	0.998	1.123	1.341	0.902	0.726	1.28	1
Korea (south)	2.008	0.7	1	0.791	3.622	1	1.348	1.308	0.905	0.458	2.501	0.995
Sri Lanka	1.386	1.13	1	0.821	1.493	1	1.503	0.845	0.921	0.877	2.203	1
Madagascar	2.435	1.09	1	3.378	0.661	1	1.27	1.236	0.878	1.452	0.807	1
Mexico	3.148	1.034	0.986	2.555	1.208	1	1.672	1.294	0.895	1.37	1.054	1
Malawi	2.479	2.177	1	1.002	1.136	1	1.729	0.817	0.868	1.905	1.279	1
Malaysia	2.571	1.005	1	1.109	2.308	1	1.453	1.023	0.897	0.889	1.774	1.004
Norway	1.107	1	0.734	0.824	1.804	1.015	1.068	1	0.819	0.951	1.428	0.96
Pakistan	2.086	0.873	1	1.504	1.589	1	1.831	1	0.913	1.602	1.253	1
Panama	1.584	1.096	1	1.235	1.171	1	1.782	1	0.904	1.076	1.821	1.006
Peru	1.772	1.508	1	1.635	0.719	1	1.566	0.872	0.901	1.191	1.672	1
Philippines	1.824	1.396	1	1.18	1.107	1	1.359	0.926	0.892	1.303	1.26	1.002
Portugal	3.041	0.986	0.85	2.077	1.791	0.976	1.724	1.662	0.772	1.012	1.327	1
Sweden	1.689	1.464	0.619	1.199	1.445	1.075	1.033	0.884	0.874	0.98	1.366	0.998
Thailand	2.781	1.101	0.998	1.195	2.147	0.987	1.636	0.988	0.89	0.989	1.869	1.007
United States	1.292	0.909	0.907	1.059	1.481	1	0.941	1.047	0.899	0.747	1.339	1
Venezuela	1.885	1.823	0.804	1.567	0.814	1.009	1.554	1.097	0.854	1.608	1.033	1

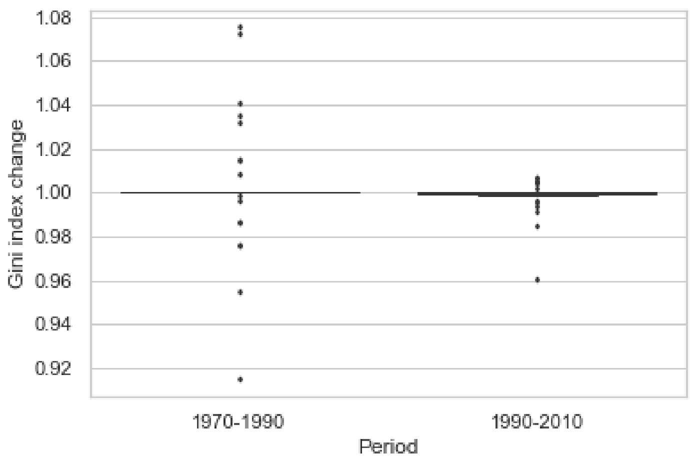
	Δ l_high	EFΔ	TCΔ	IMΔ	OMΔ	GiΔ	Δ l_high	EFΔ	TCΔ	IMΔ	OMΔ	GiΔ
Observations	33	33	33	33	33	33	33	33	33	33	33	33
Minimum	0.957	0.7	0.619	0.466	0.66	0.915	0.823	0.817	0.726	0.458	0.807	0.96
Maximum	3.326	2.177	1	3.378	3.622	1.075	1.831	1.662	0.929	1.905	2.501	1.007
St. dev.	0.626	0.306	0.109	0.596	0.573	0.028	0.275	0.198	0.05	0.313	0.341	0.008
Mean	1.886	1.166	0.926	1.351	1.478	1.002	1.39	1.116	0.873	1.047	1.455	0.999
Median	1.786	1.083	0.998	1.195	1.481	1	1.375	1.075	0.895	0.989	1.357	1

Source: Author's calculations

We need to admit that it is not completely correct to directly compare periods 1970-1990 and following 1990-2010. We need to keep in mind, that the process caught in one run of decomposition describes two moments in time. To avoid an implosion of the efficient frontier between these two periods, we need to take into consideration efficient units from the first period, which need to be components for the second-period frontier. Unfortunately, our program does not cover 3 periods so far (this is only matter of additional modification of the code), so that efficient units from the period 1970 do not enter efficient frontier in decomposition for 1990-2010, what can lead to partial distortions in continual analysis.

We start our analysis with FR decomposition of the sample of 33 countries, which is run on the periods 1970-1990 and 1990-2010. We find that inequality does not show consistently positive or negative contribution to the accumulation of human capital for the full sample of 33 countries. There is no significant feature nor for 1970-1990 period neither for the period of 1990-2010. On the other hand, if we differentiate developed OECD countries from “Others”, we find plausible results in line with existing parametric literature. Individual results for FR decomposition for period of 1970-1990 and 1990-2010 are described on Table 7.10. Results for development groups are expressed on the Figure 7.11.

Figure 7.10 Contribution of the Gini index change

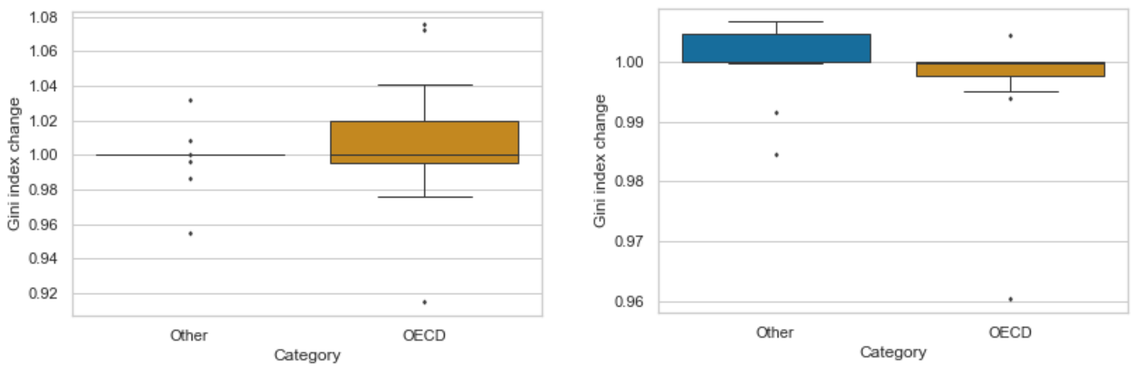


Source: Author’s calculations

We focus our attention on the distribution of all results pictured on the boxplot diagram. On the peculiar Figure 7.10, you cannot even see that mean result of the Gini index change for the first period is very slightly above 1 (1.002) and for the second period it is just slightly below 1 (0.999) what would indicate very weak positive respectively negative contribution of inequality on our sample of 33 countries. The level of standard deviation is very high in both cases to conclude any significant or systematic contribution of inequalities to the accumulation of high skills (different from 1). In average, we conclude no contribution of inequalities to the accumulation of human capital.

On the other hand, if we distinguish developed OECD countries from the group of “Others”, there is a clear indication of the contribution direction of inequality according to country development level and its trend over time. Both parts of Figure 7.11 show that the mean value for the Gini index change is still practically around 1 (nor positive neither negative contribution) in both development groups. But the dispersion of results for OECD countries is on the numbers above 1 while results for other countries mostly do not deviate from 1 in the first period. This can be interpreted that the contribution of inequalities was low for both development groups, but the effect was rather positive among OECD countries between 1970-1990. The situation changed for the period of 1990-2010. The second part of Figure 7.11 shows that contribution of inequalities on high skills was rather positive for developing countries and with rather slightly negative effect for OECD countries.

Figure 7.11 Focus on the Gini index change contribution according to country development



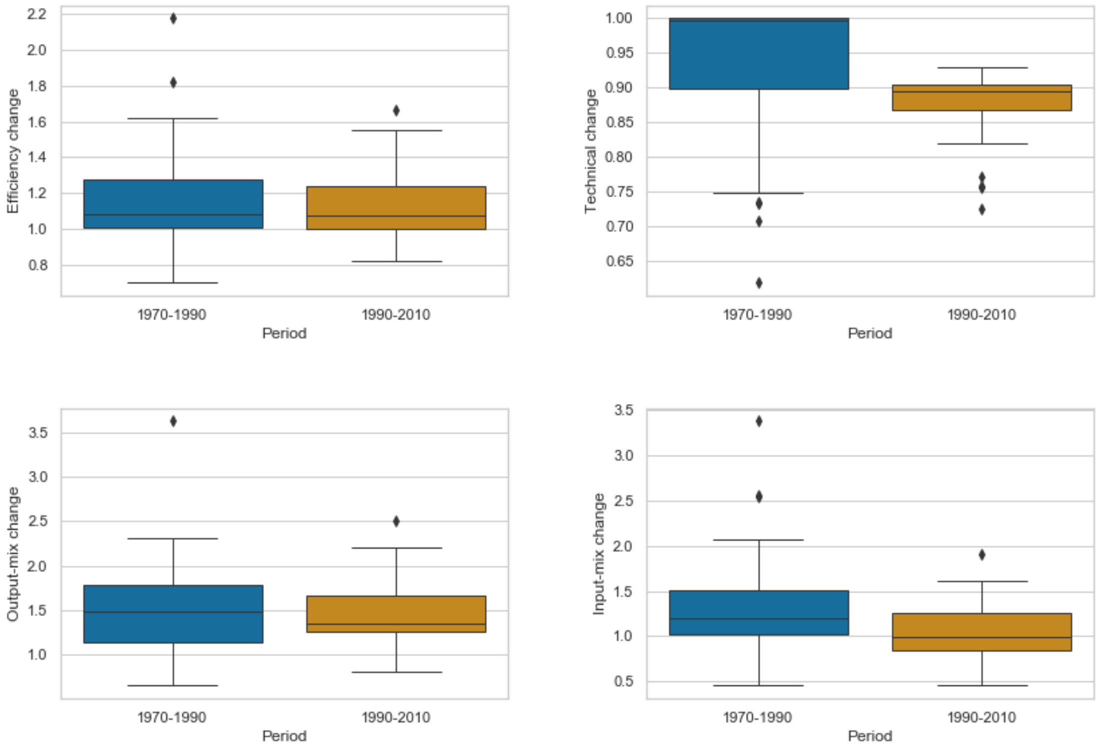
1970-1990 1990-2010

Source: Author’s calculations

A very low value for the contribution of inequality on the accumulation of human capital can be assigned to low variation in the Gini index compared to other determinant's changes over the 20-year time periods. The Gini results can be simply erased by other determinants.

Later, we find that efficiency change, and output change contribute positively to the accumulation of high-skilled labour, while technical change appears to contribute in a negative direction. Figure 7.12 later describes the contribution of the remaining four determinants on the accumulation of high skills for dataset of 33 countries. The positive contribution of efficiency change is depicted in the first quadrant. Its average results are positive values above 1 in both periods with unchanged mean of 1.116. We conclude that productivity change in the form of GDP on active population shows a strong positive effect on high-skilled labour formation. Input mix change, which contains the mix of low-skilled labour and capital stock per active population inputs, contributes slightly positive to the high skill accumulation in the first period, but with ambiguous results in the period of 1990-2010. Figure A1 in Appendix suggests that the ambiguity is present in the OECD sample while the input mix has a positive contribution to the sample of "Other" countries.

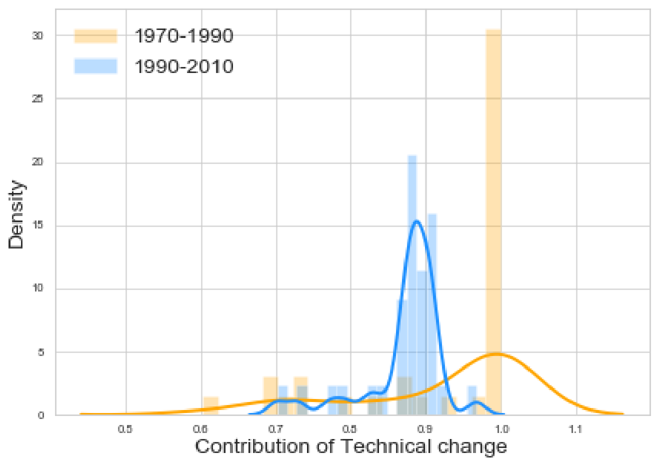
Figure 7.12 Contribution of factors to the accumulation of human capital



Source: Author's calculations

Interesting is that the technical shift seems to contribute negatively to the accumulation of high-skilled labour. This, on the first sight surprising and counterintuitive result, could be assigned to the fact that technological change has a direct impact on productivity growth (we support this hypothesis in the next HR part) with consequent potential effect on labour demand at all. Moreover, Färe et al. (2018) find in their micro-level analysis that technological shift is associated with in average negative contribution to growth in labour stock. The second quadrant of Figure 7.12 shows the technical change median effect around 1 (mean is 0.926) but with the dispersion of values in a negative direction for period of 1970-1990. Later, for the period of 1990-2010, negative results are more obvious with mean value 0.873 and low standard deviation of 0.05. The distribution of results for technical change is described better on Figure 7.13. In the first period, the most of countries resulted in a neutral contribution of technical change with most of the results equal to 1. But in the second period, these countries experienced a negative effect on the concentration of individual results around 0.9. This counterintuitively indicates that technology shift started to affect the accumulation high skills rather negatively at least in the case of our 33 countries sample.

Figure 7.13 Density of technical change contribution



Source: Author's calculations

The following part is dedicated to the next part of our two-step analysis. HR decomposition aims to look differently on the previous analysis by Henderson and Russell (2005) and apply skill level groups of labour rather than average years of schooling to the decomposition of productivity growth. Results of the second type of decomposition for individual countries are presented in the following Table 7.10. This approach brings quintipartite decomposition of economic productivity into the contribution of efficiency change, technical shift, change in capital stock and changes in the share of high-skilled and low-skilled labour.

As well as in the previous paragraphs, we apply HR decomposition on the sample of "33" countries for the time span of 1970-2010. Inspired by the broad literature about human capital importance in the second half of 20th century, we affirm consistent and positive contribution of high-skilled labour, capital stock per active population and technology

Table 7.10 HR "33" 1970-1990

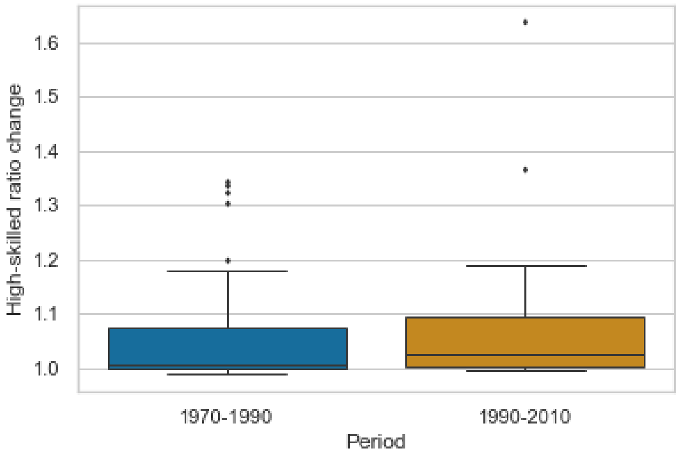
	1970 - 1990						1990 - 2010					
(33)	ΔPRO	EFΔ	TCΔ	KACΔ	l_lowΔ	l_high Δ	ΔPRO	EFΔ	TCΔ	KACΔ	l_lowΔ	l_high Δ
Argentina	0.89	0.706	1	1.33	0.948	1	1.588	1.136	1.086	1.172	0.989	1.11
Australia	1.278	1.041	1	1.347	0.868	1.049	1.466	0.93	1.101	1.459	0.98	1.001
Bangladesh	0.93	0.617	1	1.544	0.976	1	1.672	0.681	1.152	2.095	1	1.017
Brazil	1.53	0.99	1	1.539	0.974	1.032	1.229	0.969	1.094	1.099	0.989	1.066
Canada	1.36	0.99	1.077	1.296	0.915	1.075	1.265	0.877	1.108	1.313	0.989	1.003
Chile	1.092	1.316	1	1.077	0.77	1	2.022	0.961	1.076	2.095	0.929	1.005
Colombia	1.311	1.089	1	1.258	0.958	1	1.269	0.987	1.08	1.063	0.988	1.133
Costa Rica	1.154	0.784	1	1.475	0.998	1	1.475	0.927	1.062	1.414	0.993	1.067
Germany	1.515	0.975	1.104	1.444	0.984	0.989	1.367	0.897	1.113	1.352	1	1.013
Finland	1.782	1.167	1.153	1.437	0.795	1.159	1.4	0.916	1.194	1.227	0.988	1.056
France	1.531	1.117	1.262	1.132	0.818	1.173	1.284	0.772	1.315	1.07	0.994	1.188
United Kingdom	1.54	1	1.411	1.228	0.887	1.002	1.357	1	1.377	1.12	0.884	0.995
Hungary	1.818	1.031	1	2.45	0.72	1	1.265	0.82	1.103	1.433	0.975	1
Indonesia	2.245	0.903	1	2.49	0.999	1	1.712	0.857	1.058	1.783	0.978	1.083
Iran	0.66	0.62	1.095	1.123	0.722	1.2	1.168	0.885	1.172	0.976	0.987	1.168
Italy	1.615	1.1	1.296	1.093	0.771	1.344	1.218	0.648	1.316	1.054	0.992	1.366
Japan	2.01	0.84	1.009	2.593	0.895	1.022	1.28	0.746	1.109	1.565	0.988	1.001
Korea (south)	3.622	1.428	1	2.954	0.859	1	2.501	0.809	1.086	3.038	0.929	1.009
Sri Lanka	1.493	0.885	1	1.72	0.981	1	2.203	1.184	1.085	1.745	0.965	1.018
Madagascar	0.661	0.918	1	0.699	0.997	1.035	0.807	0.809	1.139	0.87	1	1.006
Mexico	1.208	0.967	1.014	1.113	0.938	1.18	1.054	0.773	1.11	1.124	0.99	1.104
Malawi	1.136	0.459	1	2.46	0.998	1.008	1.279	1.224	1.152	0.908	1	1
Malaysia	2.308	0.995	1	2.641	0.878	1	1.774	1.028	1.087	1.657	0.93	1.03
Norway	1.804	1	1.275	1.267	1.071	1.042	1.428	1	1.221	1.12	1.017	1.027
Pakistan	1.589	1.145	1	1.382	0.998	1.005	1.253	1	1.096	1.066	0.98	1.094
Panama	1.171	0.913	1	1.361	0.943	1	1.821	1	1.089	1.567	0.999	1.068
Peru	0.719	0.663	1	1.088	0.997	1	1.672	1.146	1.096	1.358	0.98	1
Philippines	1.107	0.717	1	1.551	0.997	1	1.26	1.107	1.097	1.076	0.964	1
Portugal	1.791	1.278	1.088	1.063	0.907	1.336	1.327	0.63	1.254	1.036	0.99	1.638
Sweden	1.445	0.862	1.35	1.137	0.838	1.304	1.366	1.131	1.153	1.045	0.991	1.011
Thailand	2.147	0.865	1	2.49	0.997	1	1.869	1.056	1.07	1.517	0.984	1.108
United States	1.481	1.101	1.103	1.214	0.934	1.075	1.339	0.955	1.113	1.271	0.994	0.997
Venezuela	0.814	0.578	1.232	1.057	0.818	1.323	1.033	0.912	1.167	0.9	0.992	1.088

	ΔPRO	EFΔ	TCΔ	KACΔ	l_lowΔ	l_highΔ	ΔPRO	EFΔ	TCΔ	KACΔ	l_lowΔ	l_highΔ
Observations	33	33	33	33	33	33	33	33	33	33	33	33
Minimum	0.66	0.459	1	0.699	0.72	0.989	0.807	0.63	1.058	0.87	0.884	0.995
Maximum	3.622	1.428	1.411	2.954	1.071	1.344	2.501	1.224	1.377	3.038	1.017	1.638
St. dev.	0.573	0.215	0.118	0.574	0.089	0.111	0.341	0.149	0.077	0.433	0.026	0.125
Mean	1.478	0.941	1.075	1.547	0.914	1.071	1.455	0.933	1.137	1.351	0.98	1.075
Median	1.481	0.975	1	1.347	0.938	1.005	1.357	0.93	1.108	1.227	0.989	1.027

Source: Author's calculations

change to economic productivity in the last 40 years. We also show that high skills contributed more to productivity in developed countries for the period of 1970-1990, while the coin flips in the second period of 1990-2010, when the high-skilled labour contributes more in case of non-OECD countries.

Figure 7.14 Contribution of high-skilled labour share change

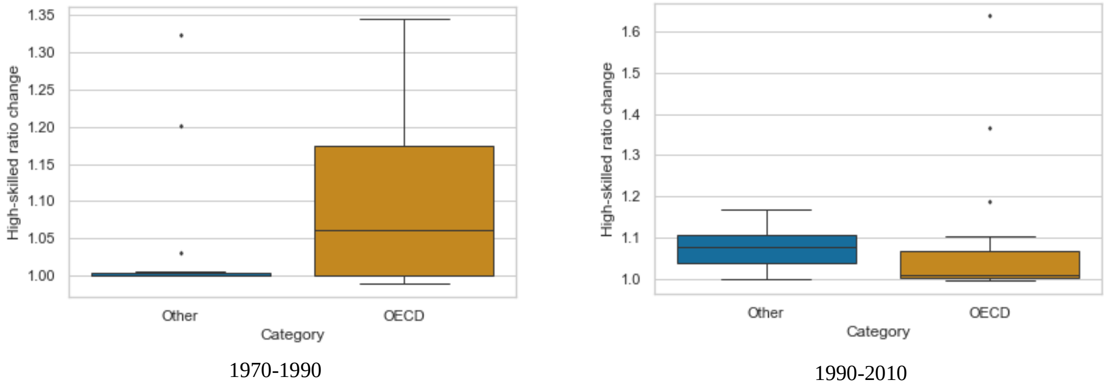


Source: Author's calculations

Firstly, we show that high-skilled labour contributes positively to the growth of economic productivity. Its contribution is presented on Figure 7.14 with mean value slightly above 1 for period of 1970-1990 and increased average contribution for the second period. We see that higher education has a positive effect on productivity in all countries except an outlier case. Dimension of country development can be followed on Figure 7.15, where it is obvious that in the period of 1970-1990 the higher education contributes more to the economic productivity of OECD countries (mean around 1.11) with minor effect in case of other countries. Later, the contribution attenuated for developed countries with already high share of high-skilled labour and non-OECD countries exhibit a slightly higher effect of high-skilled labour on productivity than OECD group during the period of 1990-2010. These results are elaborated more precisely in Section 7.2.3 on the dataset covering 161 countries for period of 1990-2010.

Results for other determinants of economic productivity are explained in Figure 7.16. We see an average negative contribution of efficiency change in the first quadrant of the table with the concentration of values in a negative area, it is true especially in the second period. This naturally indicates that if countries become less effective, it has rather a negative effect on their productivity growth.

Figure 7.15 Focus on high-skilled labour contribution

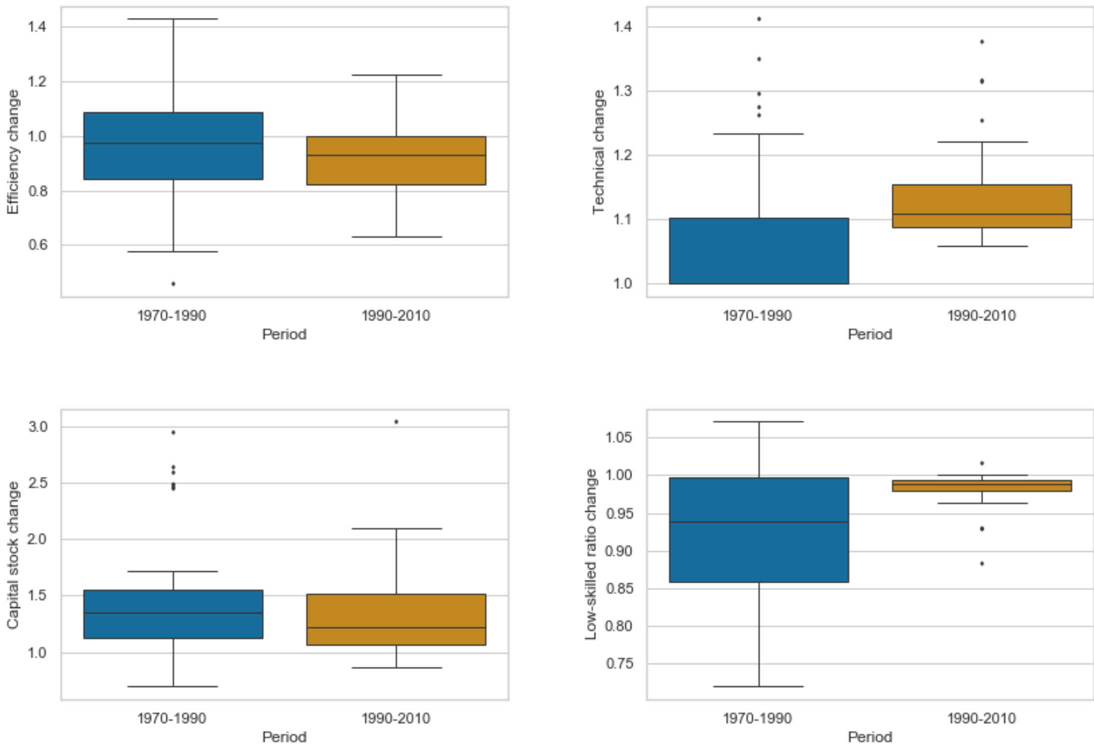


Source: Author's calculations

While the third quadrant describes consistently positive contribution of capital stock to productivity with decreasing mean over time (from more than 1.547 to less than 1.351), the fourth quadrant depicts a negative effect of low-skilled share. Negative contribution of low-skilled labour share diminishes in the second period.

Second quadrant of Figure 7.16 describes positive and increasing contribution of technical shift on productivity growth. The technical change increases on its importance in the second period, when the average contribution raised from 1.075 with robust positive tail of the distribution in 1970-1990 to the average value of 1.137 with decreasing standard deviation. This indicates that the contribution of technological shifts to productivity increases over time. Another interesting insight into the role of a technology shift is the country development dimension. Figure 7.17 indicates that while there is almost no contribution with average 1.019 of technological change on productivity progress in non-OECD countries in the first period, OECD countries exhibit robust gains from technical shift to productivity with average equal to 1.134. This gap in results partly converges in the second period with an average contribution of 1.171 for OECD and 1.104 for other countries. The probable explanation of the higher technical

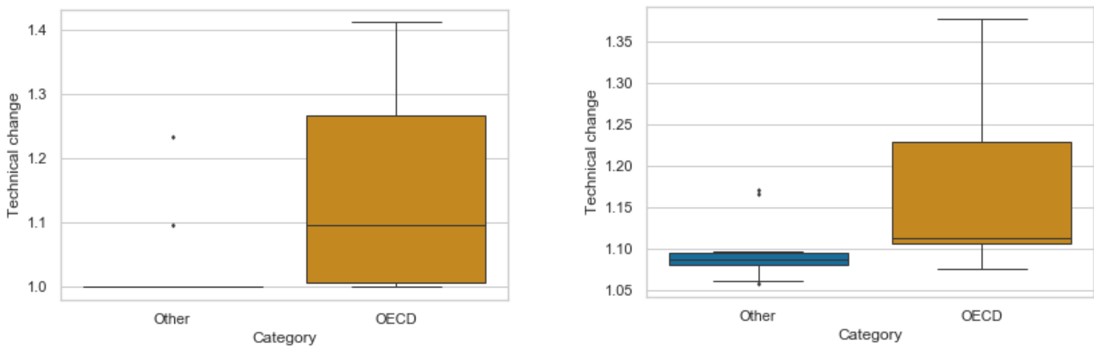
Figure 7.16 Contribution of factors to productivity change



Source: Author's calculations

shift in developed countries can be found on Figure 6.4. We can graphically follow on this figure under the settings of Henderson and Russell (2005) that the efficient frontier shifts more in the upper right quadrant, which captures mostly developed countries. The lower-left part of envelopment to which underdeveloped region is relatively compared exhibits only small movement of the frontier.

Figure 7.17 Focus on technical change contribution



1970-1990 1990-2010

Source: Author's calculations

We showed application of both decomposition equivalents on two time periods during 40 years between 1970-1990-2010. On the basic dataset of 33 countries from which around half is from OECD members group. We find the evidence about the ambiguous contribution of inequalities on human capital accumulation in the form of high-skilled labour. We showed also that development of countries matters. For underdeveloped sample, the higher inequality suggests a slightly positive effect on the accumulation of human capital, while negative for developed countries between 1990-2010. From the HR decomposition, we affirmed the persistently positive effect of high skills accumulation on productivity progress with its increasing contribution over time for developed countries. Interesting is the confirmation of technical shift importance for developed countries. We need to admit that dataset of only 33 countries is not a representative sample of world population, but we at least use the advantage that it covers full time span of 40 years. Later, we constructed dataset of 97 countries without outlier countries for more representative results at least for the time period from 1990 to 2010.

7.2.2 Results from the "79" dataset

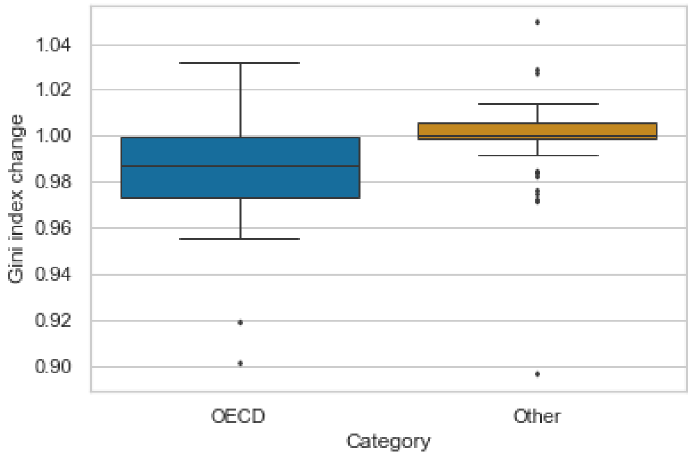
Dataset "79" is a balanced panel of countries covering all data needed to run both FR and HR decompositions on the time period between 1990-2010. This dataset does not contain usual outliers in the form of oil countries, microstates and LDC countries. We avoid its possibly unpleasant effects on efficiency frontier construction. We differentiate 33 developed OECD countries and quite heterogeneous sample of other 46 non-OECD countries.

Our results from this part mostly affirm findings from the previous section. Moreover, we find that inequality has a slightly negative contribution to high skills accumulation for developed OECD countries while non-OECD countries exhibit a neutral effect of the Gini index changes. We show these results on Figure 7.18. Three-quarters of OECD countries experience negative contribution and non-OECD countries results concentrate strictly around the value of 1. This indicates a neutral effect of inequality change on the accumulation of human capital in the case of non-OECD countries.

Contribution of the other determinants of FR quintipartite decomposition is depicted on Figure 7.19. Results from extended dataset do not provide any striking differences compared to the previous panel of only 33 countries. Efficiency change contribute to the accumulation of high skills for three-quarters of OECD countries and in one half of non-

OECD countries. Output change has a positive effect on the increase in high-skilled labour with an average result almost

Figure 7.18 Contribution of the Gini index change to the accumulation of human capital

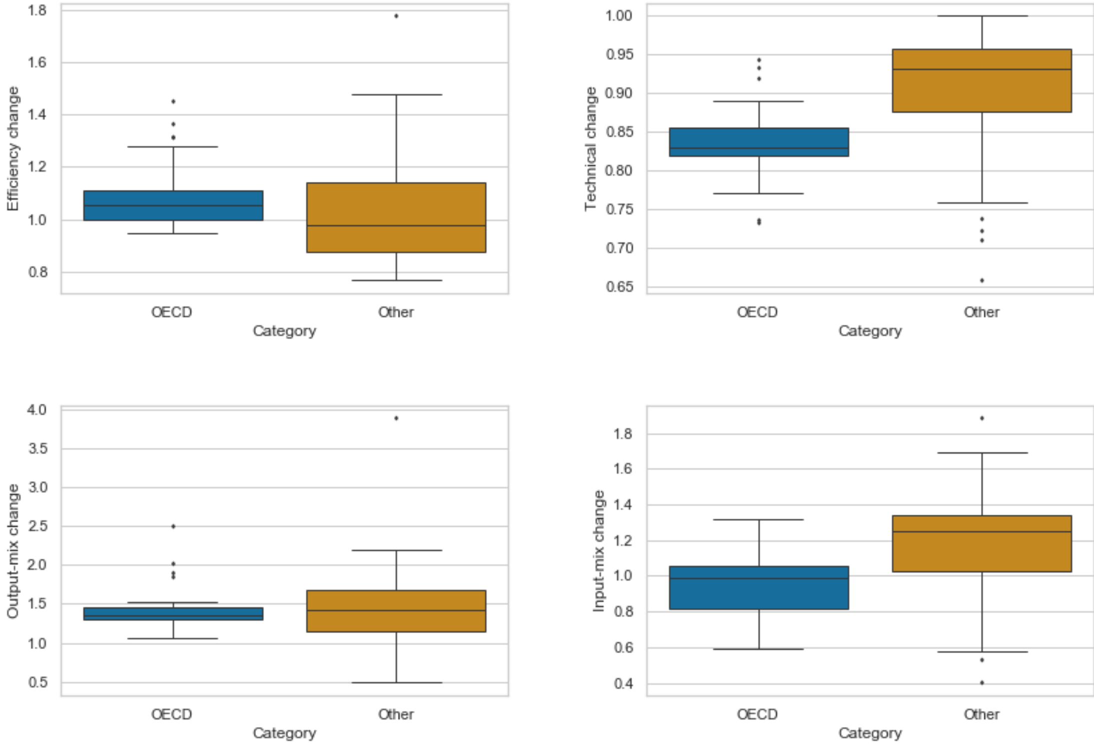


Source: Author's calculations

1.5 for both development groups, but with a higher standard deviation in case of "Other" countries. Input mix contributes negatively to the share of high-skilled labour. Three quarters of OECD countries experienced a negative and around three quarters of "Other" countries experience a positive contribution of input mix to the accumulation of high-skilled labour.

The contribution to high-skilled labour formation by technical shift is negative in all 79 countries. Figure 7.20 delivers more insights into the distribution of technical shift results and indicates that it has a stronger negative effect on high-skilled labour in developed countries. While the average result is 0.835 for a sample of OECD countries, the average contribution for "Other" countries is only 0.903. These results support the idea about the negative effect of technological improvement on labour at all described in previous Section 7.2.1. The partial explanation of why the effect is more negative on OECD countries can be probably found on Figure 6.4. While this figure follows the Henderson and Russell (2005) methodology, it clearly shows that the efficient frontier shift is more significant in its higher

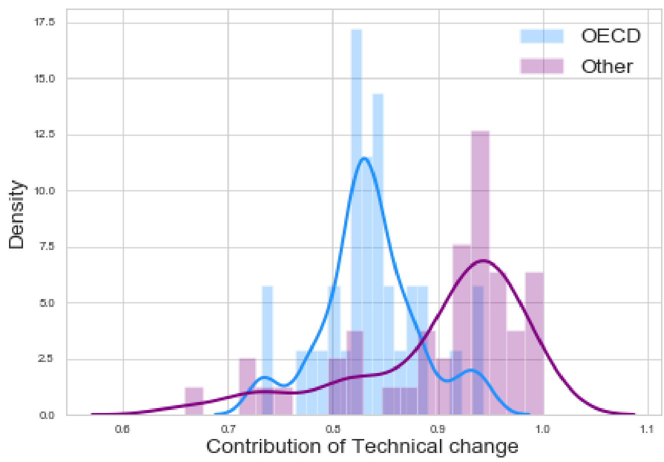
Figure 7.19 Contribution of factors to the accumulation of human capital



Source: Author's calculations

parts. In other words, developed countries experience technological improvement in higher proportion compared to the less developed world. The technological benchmark for LDCs and a big proportion of other countries, in general, does not change, which results in limited contribution of technological change to changes in other variables.

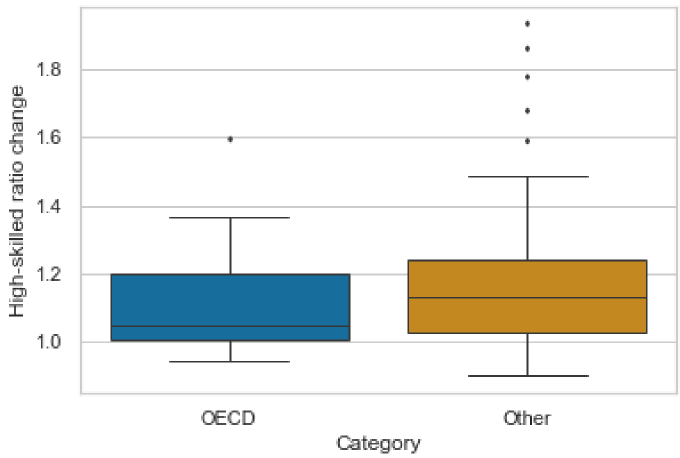
Figure 7.20 Contribution of technical change to the accumulation of human capital



Source: Author's calculations

Findings from HR decomposition from the dataset of 79 countries are presented only briefly because we extend this analysis on the panel of 161 countries in the following section and because we confirm findings from previous dataset in this part. Figure 7.21 finds positive contribution of high-skilled labour on productivity progress. We find that the average contribution is slightly higher in developing countries than in OECD sample between 1990-2010.

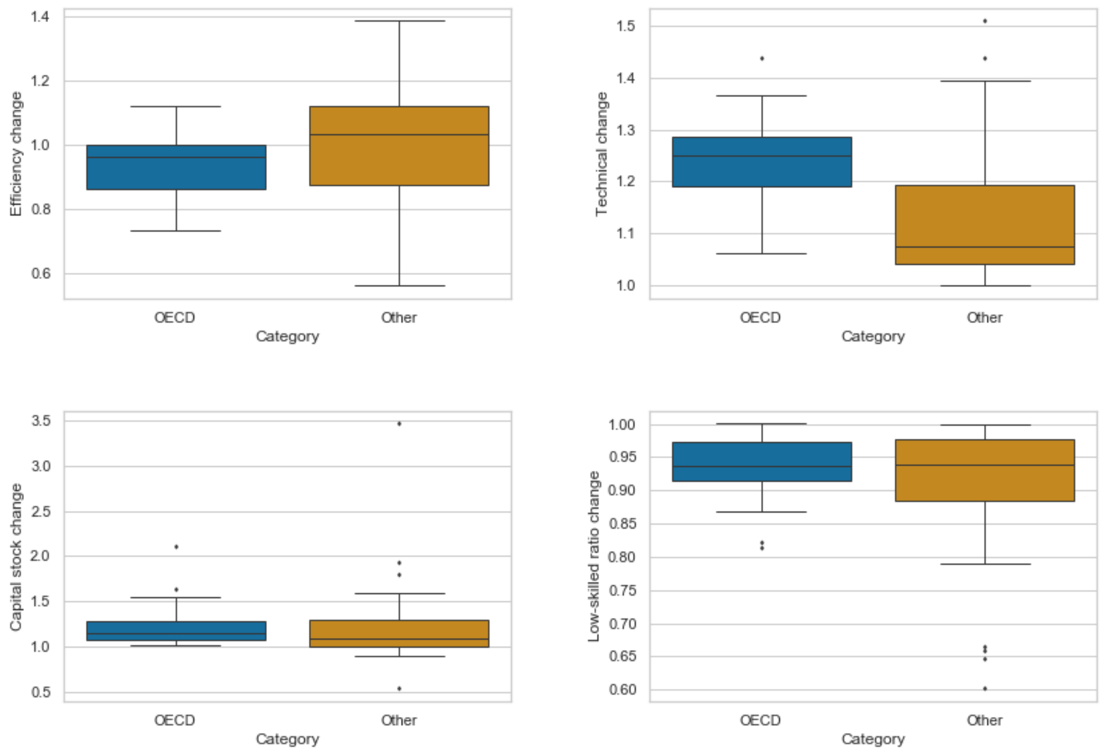
Figure 7.21 Contribution of high-skilled labour share change to productivity growth



Source: Author's calculations

Furthermore, four quadrants of Figure 7.22 explain results for contribution to productivity change by another 4 determinants. Contribution of capital stock on the active population is positive for all OECD members and three-quarters of "Other" countries. On the other hand, the effect of low-skilled labour share contributes negatively with longer negative tail in the case of non-OECD countries. Efficiency change contributes to productivity negatively in three quarters of 33 developed nations and developing countries results distribution has median close to 1. Technical shift in the second quadrant of Figure 7.22 contributes positively in both groups of countries, but the effect is more significant in OECD category.

Figure 7.22 Contribution of factors to productivity growth



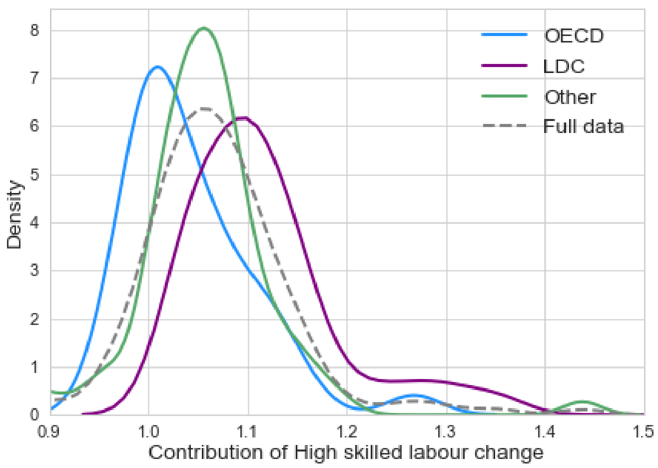
Source: Author's calculations

7.2.3 Results from the "161" dataset

Dataset of 161 countries is dedicated to the analysis of changes during the period between 1990 and 2010. Dataset "161" covers almost all world countries and territories. Panel is available only for the purpose of HR decomposition. Unfortunately, the Gini index lacks harmonisation for such a wide range of countries. Panel contains outlier oil countries, microstates and LDCs. We present our findings by highlighting the distribution of results using kernel density visualisation. We divide our dataset of 161 countries according to development level. We define a group of 36 OECD member states representing the most developed nations, a sample of 39 LDC countries according to the UN list and group of 73 "Other" countries. We do not interpret the results of 4 "Oil countries" and 6 "Microstates" in the following paragraphs, but their results are available in the Appendix.

Firstly, we focus on the contribution of high-skilled labour on productivity change. We find it in average positive for all development groups with only a few outlier countries with a negative contribution of high-skilled labour on productivity change. The negative contribution of high-skilled labour to productivity growth is always connected to negative contribution of low-skilled labour. This suggests that this finding is rather an effect of employed labour share on active population or imprecision of employment adjusted measure of high- and low- skilled labour. On the other hand, the most of countries with negative effect are former communist countries, what supports the notion about employed share on active population. For more details about countries which experienced a decrease in the share of high-skilled labour over time you can find in Appendix. Later we can recognize the increased contribution of high-skilled share for less developed countries on Figure 7.23. It shows that for OECD countries which already reached a high share of high-skilled labour in 1990, the level of high-skilled labour change contribution is minor. While the 9th decile is 1.067 for OECD countries, its value is 1.138 for "Other" and 1.244 for LDC countries, what indicates significantly higher contribution for the under-developed countries. Average contribution score is also ordered according to the development group. OECD countries exhibit in average 1.029, the value is 1.074 for other and 1.164 for LDC countries.

Figure 7.23 Contribution of high-skilled labour change to productivity growth

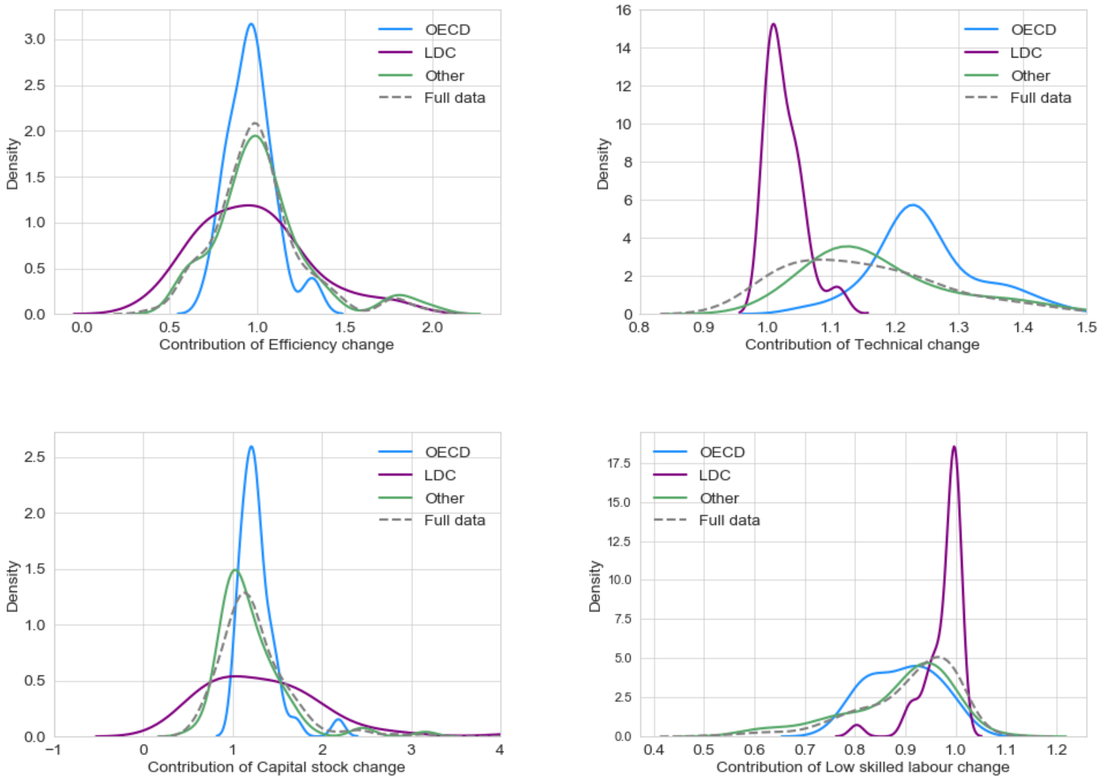


Source: Author's calculations

We summarize that the developed OECD countries with already high share of secondary and tertiary educated labour gain from this factor only slightly between 1990 and 2010. While the contribution is positive for all development groups, the highest impact is experienced in case of developing LDC countries still with the potential to increase the share of high-skilled among active population.

Contribution of other determinants to productivity growth is summarized on the Figure 7.24. Firstly, we would start with expected negative contribution of low-skilled labour share to productivity progress described in the last quadrant of Figure 7.24. In this point, it is interesting the insight from the country development dimension. Results of LDCs concentrate almost exclusively between 0.9 and 1 which indicates a slightly negative effect on productivity change by low-skilled share. Left tail of the distribution is longer for the group of “Other” countries with 10th decile around the value 0.75, with more robust tail for OECD countries with 10th decile equal to 0.812 and with the mean contribution of 0.895 for both groups. This indicates that if the country experiences an increase in the share of low-skilled population between 1990 and 2010, the effect would be more negative among developed countries.

Figure 7.24 Contribution of factors to productivity growth



Source: Author’s calculations

Efficiency change, in the first quadrant of Figure 7.24, exhibits rather a negative effect on productivity change. 3 quarters of OECD, half of other countries and more than one half of LDCs exhibit result lower than 1. We can generalize the effect of efficiency change on productivity development as ambiguous. The only difference between development groups is in the standard derivation of results (OECD: 0.139, other: 0.281 and LDCs: 0.309) what indicates the higher heterogeneity in efficiency change effect among lower developed economies.

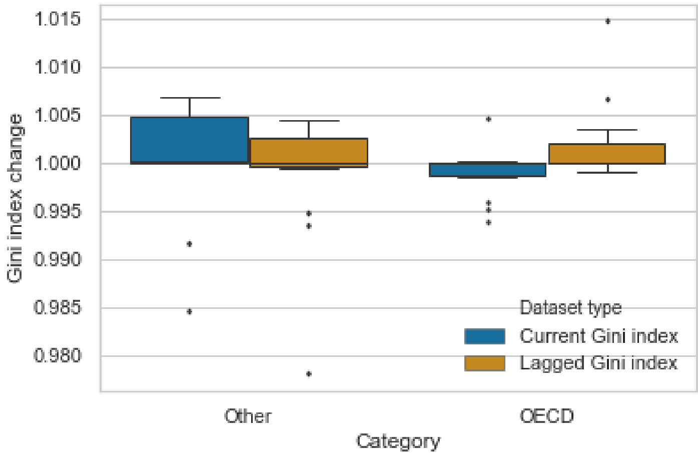
Very similar tendency occurs in the case of capital stock per active population with results in the third quadrant of Figure 7.24. Again, the variation in the contribution is the highest for LDCs (st. dev. 1.17) with the lowest dispersion of its values in the case of OECD countries (st. dev. 0.206). Later, all OECD countries experienced positive contribution of capital stock on productivity change, which is not true for LDCs and group of "Other" countries. Strikingly intuitive results are provided by the HR decomposition for the contribution of technological change. We demonstrate that technological change has almost no contribution to LDC countries, mild for a sample of "Other" countries and the highest positive contribution for OECD countries. While the mean contribution for the OECD group is around 1.272 (st. dev. 0.111) and the mean of "Other" countries is 1.218 (st. dev. 0.213). The average contribution of technology to productivity of LDCs concentrates around 1.029 (st. dev. 0.026). This indicates that while the efficiency change has an ambiguous contribution to all development groups, the shift of technological frontier exhibits rather a neutral effect on less developed countries and significantly positive contribution to productivity of the developed world.

The following section is dedicated to further findings from FR decomposition. We find that the relation between change in the Gini index and the contribution to the high-skilled labour. We also provide further results for verification of the hypothesis that inequality would affect the accumulation of high skills with a lag of 20 years.

7.2.4 Lagged Gini analysis

According to inequality of opportunity literature, the inequality enters the process of human capital accumulation in the childhood of an individual. Following this argument, it is worth to verify whether the 20-year lag in disposable income Gini index would affect our results differently. We apply this principle on the period of 1990-2010. We use all variables from these two periods, but the lagged Gini index in 1990 is from the year 1970 and the Gini index for the period 2010 is from the year 1990. We simply assume that the inequality 20 years ago would enter the decision making about the future education, which becomes a part of production function with 20-year lag.

Figure 7.25 The contribution of the lagged Gini index change according to the country development group between 1990-2010



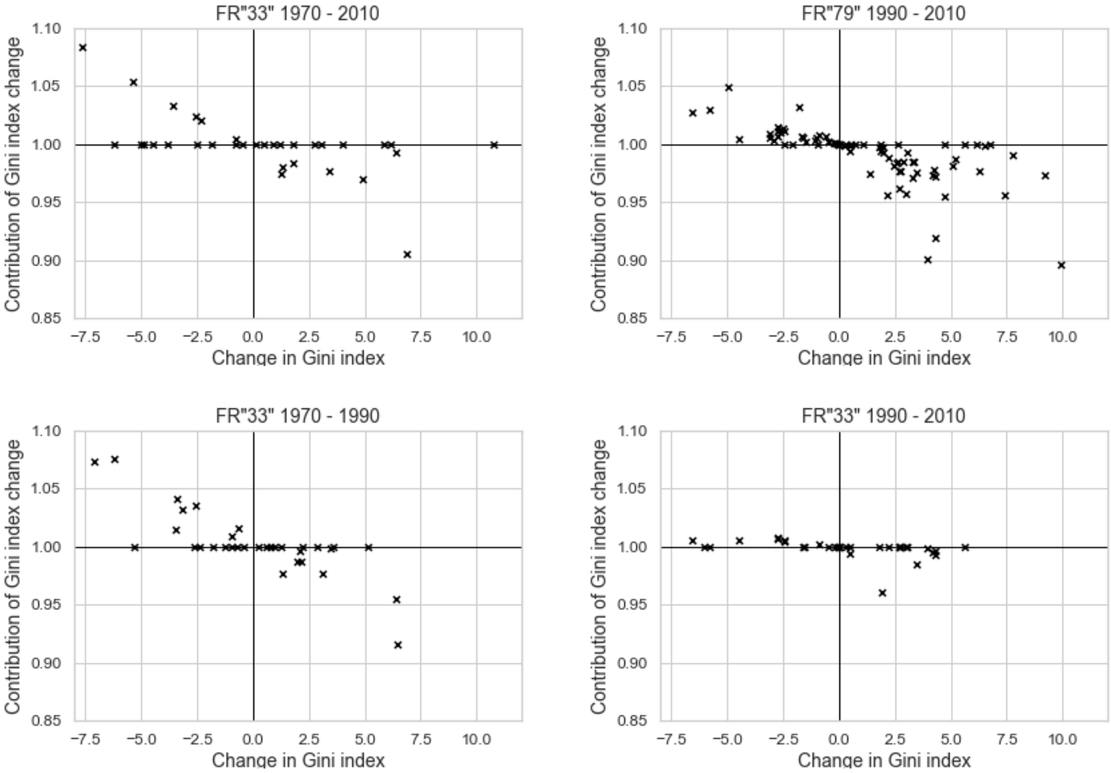
Source: Author's calculations

Figure 7.25 shows that regarding the group of 14 "Other" countries that the contribution of the lagged Gini index has a lower positive contribution to the accumulation of human capital than in the case when using current Gini index. On the other hand, the result in the case of 16 OECD countries, the direction of the Gini index contribution has changed. While the contribution is rather negative for the decomposition with current Gini index, three quarters of results from decomposition with lagged Gini index provide positive contribution to the accumulation of high skills. These results are unfortunately run on the small and heterogeneous sample. Moreover, the questionable is a length of the lag. The lag would probably require additional analysis about the country specific average years of schooling. We would assume that decision about the higher level of education could vary depending on the limit of usual average length of study program in a certain country.

7.2.5 Gini effect

Finally, we would like to conclude also, that contribution of inequality exhibits systematic feature between country change in the Gini index and its contribution to high skills formation. If there is a decrease in the Gini index over time, its contribution is positive or there is no contribution with a result equal to one. On the other hand, if the level of inequality rises between two time periods, it contributes negatively to the accumulation of human capital or there is no effect. You can see this feature in all 4 cases we apply FR decomposition on Figure 7.26.

Figure 7.26 Relation between the change in Gini index and its contribution to the accumulation of human capital



Source: Author's calculations

This finding is in line with inequality literature dedicated to social mobility and theory of Galor and Zeira (1993). Increased inequality contributes inversely to the accumulation of high skills or, in general, to the accumulation of human capital This finding is treated rather as an observation from our DEA decomposition and as a proposition for further research than as the final conclusion or evidence of causality. Anyway, taking into consideration non-parametrically constructed efficient frontier and its shift over time, as well as accounting for movement of a DMU toward or away from this benchmark, and together with the effect of other determinants, we find inverse or no contribution effect of inequality change to the accumulation of high skills.

8 Discussion and Conclusion

The last chapter is dedicated to the summary of findings from this dissertation thesis and to a description of methodological challenges or potential improvements of our work.

8.1 Discussion

We tried to contribute to a topic which is already covered well by parametric approaches. Introducing a different approach to the existing discussion is always followed by a fruitful debate. This section is dedicated mainly to the discussion of certain aspects and methodological challenges in this dissertation thesis. Most of these challenges are assigned to the non-parametric DEA approach, which is used to compose an efficient envelopment of countries. This way, we bring the aspect of the contribution of the technology shift and movement towards or away from the efficient frontier into the discussion. The following modifications of intertemporal decompositions allows us to perform an additional analysis of the contributions between certain inputs and outputs, but we need to be aware of the limitations of our methodology.

Following the recent literature, we need to admit, that the Gini index does not have the best ability to fully cover the distribution of resources in the economy among the pool of inequality indicators. As we explain in Section 2.2, the Gini index does not change much in time, which makes it complicated to capture its effect on other variables. What is more, the Gini index is not capable of indicating certain shifts of income between distribution groups (Nežinský and Luptáčik, 2019). Our dissertation has the ambition to cover 40 years of development, and that is why the Gini indicator is the only option in terms of the historical availability of data. Our analysis does not cover other indicators, which could shed more light at least at the reduced time span of 1990-2010. We provide a comparison of different sources of the Gini index in Section 7.1.3., which provides an indication of the skewness of the SWIID database. Because we use the simple Gini index, our analysis may not capture fully the effect of inequalities on the accumulation of high-skilled labour.

Following the methodology of the decomposition by Färe et al. (2018) and later by Henderson and Russell (2005), we used the basic DEA model with constant returns to scale. The introduction of a radial DEA model with variable returns to scale, which also takes into account the potential effect of the economy size, could probably improve our analysis. Another extension would be using the advantage of the non-radial slack based model which could reveal the potential complication of a weak efficiency and ignore the radial orientation on inputs or outputs (Cooper et al., 2007).

Probably the main weakness of the DEA approach is its sensitivity to heterogeneous samples and outlier countries. In DEA, it is common to select a sample of countries or DMUs which does not contain outliers. If outlier scores were efficient, it could influence the efficient frontier with an implausible effect on efficiency scores and thus also on the decomposition results. This weakness could be relevant mainly in the dataset of "33" countries, where we are limited to the selection of a more homogeneous sample. For this reason, we avoid outlier countries in the dataset of 79 countries which does not provide results different from other datasets. The "79" dataset is probably still quite heterogeneous even when we get rid of the usual outliers of oil countries, city-states and LDCs. We ran a robustness check on the sample "79" which provides evidence about a minor effect of outliers on the decomposition results of inefficient countries. The reason for this are the numerous counterfactual simple DEA models which enter a single decomposition score so that the outlier input or output feature is spread among these counterfactuals and does not affect the score as in the case of a simple model. On the other hand, a heterogeneous sample allows us to extend our simple decomposition by the dimension of country development groups. To deal with heterogeneous samples, it is common practice in DEA to apply the comparison of systems, which allows us to compare efficient frontiers between different groups with homogeneous technologies (Cooper et al., 2007).

Unfortunately, described in Figure 6.5, our analysis of the "33" dataset does not provide a continuous intertemporal analysis of all 3 time periods. Our decomposition takes into consideration a prohibition of the efficient frontier implosion, but only between two points in time. That is why our actual model treats only a time span of 2 periods instead of 3. For this reason, it is not completely correct to directly compare the development in 1970-1990 and 1990-2010 as a continuous process. This issue could be solved through further extension of the model.

Later, there is a possibility to modify our approach in the way we treat a bad output in the form of the Gini index. We could alternatively treat inequality as an input or as a good output. It is common practice in DEA analysis to convert a bad output to behave as a good output, so we could take the Gini index as a positive index 1- Gini.

Furthermore, the question is how we adjust the active population by employment rate in Section 7.1.2. We use the same employment rate for both skill groups, which, as we explained, is not the ideal option, but because of the limitation of historical data, we decided to use this sub-optimal measure in the DEA analysis of high- and low- skill groups, the sum of which is not 1. This aspect could not be in line with our DEA assumptions and we would need to account for mobility of labour force between countries, which is not captured in the VID-IIASA database.

Nevertheless, our non-parametric decomposition follows methodological standards from previous DEA literature. Our modifications allow us to analyse linkages between inequality and the accumulation of high skills and consequently between the high skills and growth of productivity. In the next section, we present our conclusions and specify our contribution to the existing research into this topic.

8.2 Conclusion

In this section, we summarize our findings and specify our contribution into the literature about the interrelation between inequality, human capital formation and economic growth. Our contribution is based on introducing the technological frontier defined by the DEA model to this issue. In particular, we modified non-parametric decompositions by Färe et al. (2018) and Henderson and Russell (2005) to reveal the contribution of inequality to high skills formation in the first step and then we analyses the contribution of high-skilled labour to economic productivity. In other words, we used the advantage of the DEA methodology and took into consideration also the effects of technological frontier shift, efficiency change impact, output mix and input mix change, as we explained in the methodology section. In the following paragraphs, we present findings from modified intertemporal decompositions, which may bring a new aspect into the literature covered well by parametric methodology.

Firstly, the findings from Section 7.2.5 about the FR decomposition on datasets "33" and "79" indicate that inequality development systematically contributes to the accumulation of high-skilled labour. In general, we observe the inverse feature between the change in Gini index and its contribution to the accumulation of high skills. If the Gini index decreases over time, its contribution to high skills is positive or neutral (with a result equal to one or higher). On the other hand, if the level of inequality rises between two time periods, it contributes negatively to the accumulation of human capital or there is no effect (with a result equal to one or lower). In general, these results indicate the expected direction following the results of recent inequality literature that the relationship between inequality and the accumulation of high skills, with many countries with no effect.

Secondly, in line with the recent parametric literature, we see changes in the effect of inequality on the accumulation of high-skilled labour over time and among country development levels. In general, the contribution of inequality on the stock of high skills is rather neutral for the full sample of countries, but if we differentiate the development level of countries, we recognize an interesting feature between development groups. In the first period of 1970-1990, OECD countries exhibit a slightly positive effect of inequality on the accumulation of human capital in line with the model by Galor and Moav (2004). Later, the contribution becomes rather negative in most of the developed countries in the 1990-2010 period. Following underdeveloped countries, the contribution of inequality is concentrated strictly around 1, which indicates no effect of inequality on the stock of high skills in 1970-1990. Later, the contribution becomes slightly positive in the second period of 1990-2010. This is in line with development theories, which consider inequality beneficial in early stages of development, but with a negative effect on the accumulation of education in later development stages, when education becomes an engine of economic development.

The last insight to the analysis between inequality and the accumulation of high skills was based on the simple introduction of lagged inequality measure into the intertemporal analysis. This idea followed the theory about the inter-generational transmission of inequalities, but it would require a more detailed analysis of regional differences in the length of lag and education costs in future research. If we introduced the effect of the Gini index with a 20-year lag to the "33" panel, the contribution would change for both development groups. Section 7.2.4 provided a piece of evidence that the lagged Gini index for "Other" countries would decrease the positive effect in the most countries in 1990-2010, but in the case of developed countries, the slightly negative contribution in 1990-2010 period would change its direction to rather a positive contribution to high skills with the lagged Gini index.

Naturally, in the second step of our analysis, the HR decomposition confirmed findings about the positive contribution of high skills to economic productivity. All four HR decompositions provided a piece of evidence in favour of this hypothesis and showed a negative contribution of low-skilled labour on productivity. From the point of view of the HR decomposition, it is more interesting to follow the differences in the distribution of results according to time and country development.

In this step, we analysed the contribution of high-skilled labour on economic productivity. The HR decomposition employed a different model than the FR decomposition. The HR model did not incorporate the Gini index. The effect of inequality entered the model through the stock of high skills. Firstly, the "79" dataset mostly validated findings from the decomposition on the previous sample of "33" countries. The analysis of the 1970-1990-2010 timeframe provides arguments for the decreasing positive contribution of high skills to economic productivity in the case of developed countries and the increasing positive impact of high-skilled labour on the productivity of underdeveloped regions. Specifically, in the period of 1970-1990, higher education contributed more to the economic productivity of OECD countries and only had a minor effect in the case of other countries. Later, the contribution attenuated for the developed world with an already high share of high-skilled labour and non-OECD countries exhibited a slightly higher contribution of high-skilled labour to productivity during the period of 1990-2010 than the OECD group.

Later, we analysed the development aspect through the HR decomposition more deeply. The "161" dataset provided a wide sample of world countries between 1990-2010 and confirmed findings on a more granular level. If we differentiate OECD, LDC and “Other” country groups, we find that the positive contribution of high skills is the highest in the case of the least developed countries, lower among the group of other countries and still positive, but the lowest for the developed OECD countries. The situation is reversed for technical shift contribution to productivity. Movement of the technological frontier has the most significant positive contribution to productivity in developed countries, lower with a wide dispersion of results for “Other” countries and a very limited positive contribution of technology improvement for LDCs.

Finally, we would like to sum up our findings. We showed that hat the nonparametric approach which, in comparison to parametric methodology, introduces a technological frontier type of analysis, can provide a new insight into the literature about the interrelationship between inequality, the accumulation of human capital an economic growth. This dissertation thesis only presented the general results of our decompositions, but indicated results were very similar to the majority of inequality and economic growth literature. As well as parametric methods, we summed up the positive effect of high skills on the growth of economic productivity, with a higher potential among the less developed world in recent decades. Later, we found a higher effect of the technology frontier shift on productivity growth among developed countries. And finally, we also summarized the low effect of inequalities on the accumulation of high-skilled labour, which contributed to high skills stock positively in the case of OECD countries in the 1970-1990 period and on the underdeveloped world. What is important is the negative effect of inequality on high-skilled labour in the case of developed countries between 1990-2010. This result is in line with the very recent inequality literature, which provides strong evidence that inequality harms economic growth through a reduced accumulation of human capital in modern developed countries.

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