Innovation, reallocation, and growth in the 21st century

Elias Einiö, Heli Koski, Tero Kuusi, Markku Lehmus

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Abstract

Our work applies the model developed by Acemoglu et al. (2018), henceforth, *AAABK*, for assessing the growth and welfare implications of different types of innovation policies. Central to the AAABK model is the ratio of high-productivity and low-productivity firms in total output and how different policy measures affect this relationship.

We employ the AAABK framework in order to build a macroeconomic model of the innovative business sector in Finland and fit it to the company-level micro-data on Finnish companies from 2000 to 2016. Acemoglu et al. (2018) employed US data from the 1980s and 1990s. We complement their work by estimating the AAABK model for more recent years: 2000–2016. Our results add to the literature by providing evidence on the aggregate effectiveness of innovation policies in this more recent period of slower economic growth.

Our empirical findings yield, by and large, similar qualitative conclusions on the effects of public policies on economic growth and welfare to those reported in the original work using the US data. Generally, increasing R&D subsidies would be a recommendable policy. The welfare impacts of R&D subsidies are highest when they accelerate the re-allocation of R&D workers to companies with high R&D productivity. The most effective innovation policy targets R&D subsidies to companies with the highest innovation capacity (i.e., in these companies, R&D employees generate the highest increase in a firm's productivity). If subsidies are allocated to companies with low innovation capacity or to low-productivity companies that are close to exiting the market, there will be less innovation and slower economic growth.

Provision

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Keywords

Business subsidies, innovation, innovation policy, growth, growth models, research, research activities

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Kieli	Englanti	**Sivumäärä**	56

Tiivistelmä

Tutkimuksemme soveltaa Acemoglun ym. (2018) kehittämää mallia (AAABK-malli), joka mahdollistaa erilaisten yrityssektoriin kohdennettujen politiikkatoimien kokonaistaloudellisten vaikutusten arvioinnin. Keskeistä AAABK-mallissa on korkean ja matalan tuottavuuden yritysten suhde kokonaistuotannosta ja se, miten eri politiikkatoimet vaikuttavat tähän suhteeseen.

Rakennamme Suomen yrityssektoria kuvaavan makrotaloudellisen mallin ja sovitamme sen vastaamaan Suomen yrityskenttää käyttämällä yritystason mikroaineistoa suomalaisista yrityksistä vuosilta 2000-2016.

Suomen talouteen sovitettu malli tuottaa samanlaisia laadullisia johtopäätöksiä yritystukien vaikutuksista talouskasvuun ja hyvinvointiin kuin AAABK:n Yhdysvaltojen taloutta koskeva analyysi. T&k-tukien määrän kasvattaminen olisi kannattavaa. Tukien kokonaistaloudelliset hyödyt ovat suurimmat, kun tuet kiihdyttävät t&k-työntekijöiden siirtymistä yrityksiin, joiden t&k-toiminnan tuottavuus on korkea. Tehokkainta innovaatiopolitiikkaa on t&k-tukien kohdentaminen yrityksille, joiden innovaatiokapasiteetti on korkein, eli joiden käytössä t&k-työvoima tuottaa suurimmat lisäykset yrityksen tuottavuuteen. Mikäli tuet kohdennetaan matalan innovaatiokapasiteetin yrityksiin tai lähellä markkinoilta poistumista oleviin matalan tuottavuuden yrityksiin, syntyy innovaatioita vähemmän ja talouskasvu on hitaampaa.

Klausuuli

Tämä julkaisu on toteutettu osana valtioneuvoston selvitys- ja tutkimussuunnitelman toimeenpanoa.(tietokayttoon.fi) Julkaisun sisällöstä vastaavat tiedon tuottajat, eikä tekstisisältö välttämättä edusta valtioneuvoston näkemystä.

Asiasanat Yritystuet, innovaatiot, innovaatiopolitiikka, kasvu, kasvumallit, tutkimus, tutkimustoiminta

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Innovation, kreativ förstörelse och tillväxt på 2000-talet

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I vår undersökning använder vi den av Acemoglu et.al. (2018) utvecklade modellen (AAABK-modellen), som möjliggör utvärdering av de totalekonomiska effekterna av olika policyåtgärder som riktats mot företagssektorn. Centralt i AAABK-modellen är förhållandet mellan företag med hög produktivitet och företag med låg produktivitet i totalproduktionen och det, hur olika policyåtgärder inverkar på det här förhållandet.

Vi bygger upp en makroekonomisk modell som avbildar Finlands företagssektor och anpassar den till att motsvara Finlands företagsfält genom att använda mikrodata på företagsnivå från finska företag från åren 2000-2016.

Modellen som anpassats till Finlands ekonomi leder till likadana kvalitativa slutsatser om företagsstödens effekter på den ekonomiska tillväxten och välfärden som AAABK:s analys gällande USA:s ekonomi. Det skulle vara lönande att öka mängden FoU-stöd. Den totalekonomiska nyttan av stöden är störst, när stöden framskyndar överflyttningen av FoU-anställda till företag, vars FoU-verksamhet har en hög produktivitet. Den mest effektiva innovationspolitiken är att rikta FoU-stöden mot företag, vars innovationskapacitet är högst, d.v.s. hos vilka FoU-anställda genererar den största ökningen i företagens produktivitet. Ifall stöden riktas mot företag med låg innovationskapacitet eller mot företag med låg produktivitet som är nära att träda ut från marknaden, så resulterar det i att det uppstår färre innovationer och den ekonomiska tillväxten är långsammare.

Klausul

Den här publikation är en del i genomförandet av statsrådets utrednings- och forskningsplan.(tietokayttoon.fi) De som producerar informationen ansvarar för innehållet i publikationen. Textinnehållet återspeglar inte nödvändigtvis statsrådets ståndpunkt.

Nyckelord

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Contents

LUKIJALLE

Viimeisen vuosikymmenen heikko tuottavuuskehitys ja laskeneet t&k-panostukset ovat nousseet huolenaiheeksi monissa Suomen taloudellista tilaa ja tulevaisuuden näkymiä koskevissa keskusteluissa. Syytä huoleen onkin, koska innovaatiot ja tuottavuuskasvu ovat kilpailukykymme ja hyvinvointimme kannalta ratkaisevia tekijöitä.

Bruttokansantuotteeseen suhteutettujen tutkimus- ja kehitysmenojen lasku 2010-luvulla aiheutui suurelta osin yrityssektorin t&k-intensiteetin supistumisesta vajaasta kolmesta prosentista 2,1 prosenttiin. Koska tutkimus- ja kehityspanostukset ovat tärkein tuottavuuskasvua määrittävä tekijä, tarve löytää keinoja saada t&k-menot kasvu-uralle on suuri. Hallitus on asettanut tavoitteekseen nostaa t&k-menot neljään prosenttiin BKT:sta vuoteen 2030 mennessä. T&k-tuet ovat taloustieteellisen tutkimuksen mukaan eräs parhaimmista innovaatiokannustimista yrityksille. Toisaalta t&k-tukien kuten myös muiden innovaatiopoliittisten keinojen vaikutuksesta koko talouden kasvuun ja hyvinvointiin tiedetään verrattain vähän.

Tämän hankkeen päämääränä on ollut tuottaa tietoa yritystukien kokonaistaloudellisista vaikutuksista. Tieto on olennaisen tärkeää tehokkaan tukipolitiikan suunnittelussa ja elinkeinopoliittisten toimenpiteiden toteutuksessa. Vastaavanlaisia tutkimuksia on raportoitu maailmalla vain vähän ja harjoitus on ensimmäinen suomalaisella aineistolla tehty.

Kiitämme hankkeen ohjausryhmää ja sen puheenjohtajaa Markku Stenborgia sekä hankkeessa neuvonantajina toimineita Ari Hyytistä, Niku Määttästä ja Tuomas Takaloa hyvistä ja rakentavista kommenteista ja keskusteluista.

Tutkimusryhmän puolesta Heli Koski
Joulukuussa 2021

Tiivistelmä

Yritystukien kokonaistaloudellisten vaikutusten ymmärtäminen on olennaisen tärkeää tehokkaan innovaatiopolitiikan suunnittelussa ja elinkeinopoliittisten toimenpiteiden toteutuksessa. Yritystuet vaikuttavat yrityssektorin uusiutumiskykyyn ja sitä kautta tuottavuuden kasvuun ja kilpailukyvyn kehitykseen. Suorien vaikutusten lisäksi kokonaistaloudellisiin vaikutuksiin sisältyvät tukien epäsuorat vaikutukset muihin yrityksiin läikkymismekanismien (mm. tiedon leviäminen) ja markkinahintojen (mm. työvoiman hinta) kautta. Lisäksi tuet vaikuttavat joko vahvistavasti tai heikentävästi tuottavuuden kehitykseen sen kautta kohdentuvatko ne matalan vai korkean tuottavuuden liiketoimintaan. Onnistuneella yritystukipolitiikalla voidaan kiihdyttää talouden kasvua ja kilpailukyvyn parantumista. Toisaalta tuet voivat pahimmassa tapauksessa hidastaa tuottavuuskasvua.

Tutkimuksemme soveltaa Acemoglun ym. (2018) kehittämää mallia (AAABK-malli), joka mahdollistaa erilaisten yrityssektoriin kohdennettujen politiikkatoimien kokonaistaloudellisten vaikutusten arvioinnin. AAABK-mallin avulla voidaan arvioida erityisesti taloutta uudistavien tukien (t&k-tuet) kokonaistaloudellisia vaikutuksia. Malli huomioi tukien suorien kannustinvaikutusten lisäksi epäsuorat vaikutukset, jotka syntyvät tiedon läikkymisen ja markkinahintojen muutosten seurauksena. Malli tuottaa kvantitatiivisen tuloksen myös politiikkatoimien hyvinvointivaikutuksista. Analyysi tuottaa johtopäätöksiä myös ”säilyttäviä”, muita kuin yritysten innovaatiotoiminnan kustannuksia laskevia tukia painottavan tukipolitiikan seurauksista (s. 38).

Keskeistä AAABK-mallissa on korkean ja matalan tuottavuuden yritysten suhde kokonaistuotannosta ja se, miten eri politiikkatoimet vaikuttavat tähän suhteeseen. Mallin makrotaloudellisessa analyysikehikossa politiikkatoimien aiheuttamat hintamuutokset huomioidaan kansantalouden panos- ja tuotemarkkinoiden tasapainottumisen kautta. Malli havainnollistaa erityisesti sitä, että kansantalouden tuottavuuskasvua määrittää olennaisesti osaavan työvoiman määrä tutkimus- ja kehitystoiminnassa (t&k) korkean t&k-tuottavuuden (ts. korkean *innovaatiokapasiteetin*) yrityksissä.

Tutkimuksessamme rakennetaan Suomen yrityssektoria kuvaava makrotaloudellinen malli seuraten Acemoglun ym. (2018) teoriakehikkoa. Malli sovitetaan vastaamaan Suomen yrityskenttää käyttämällä yritystason mikroaineistoa suomalaisista yrityksistä vuosilta 2000-2016. Aineisto kattaa noin 99% koko talouden t&k-investoinneista. Toisin kuin Acemoglun ym. (2018) käyttämä aineisto, kotimainen yritystason tilasto on kattava myös pienempien yritysten osalta. Tämä mahdollistaa mallin sovittamisen koko taloudelle, eikä vain suuremmille yrityksille.

Acemoglun ym. (2018) malli sovitetaan Suomen talouteen ns. simuloitujen momenttien menetelmän avulla. Menetelmä on tiivistetysti seuraavanlainen. Ensin suomalaisesta mikroaineistosta lasketaan yritysten kasvua, poistumista, t&k-toimintaa ja työvoiman käyttöä kuvaavia tilastollisia suureita – analyysissämme nämä ovat keskiarvoja. Lisäksi aineistosta lasketaan kokonaistaloudellinen kasvuaste. Tämän jälkeen teoreettista mallia vastaavasta ohjelmallisesti rakennetusta numeerisesta mallista lasketaan vastaavat tilastosuureet suurelle joukolle mallin eri parametriarvoja. Teoreettisen mallin parametrien estimaateiksi valikoituvat ne, jotka tuottavat näissä simuloinneissa tilastoaineistosta laskettuja tilastollisia suureita parhaiten vastaavan tuloksen.

Hankkeessa tarkasteltiin sekä (1) yksinkertaisia tukipolitiikkoja, joissa tukia ei kohdenneta yritysten t&k-toiminnan tuottavuuden perusteella että (2) valikoivia tukipolitiikkoja, joissa tukea jaetaan t&k-toiminnan tuottavuuden perusteella. Käytännön innovaatiopolitiikassa valikoimattomat tuet lähestyvät luonteeltaan neutraaleja t&k-verotukia, jotka eivät kohdennu tietynlaisille yrityksille tai hankkeille. Tukea saavat yritykset valitsevat tutkimushankkeet maksimoidakseen markkinoilta saatavan tuottonsa. Yksinkertaista tukipolitiikkaa voidaan perustella sillä, että käytännössä yritysten t&k-toiminnan tuottavuutta on vaikea havaita. T&k-verotukien tavoitteena on suoria tukia neutraalimpi t&k-toiminnan volyymin ja tuottojen kasvattaminen. Analyysissamme tarkastellut valikoivammat politiikkatoimet sisältävät sen sijaan suorien tukien piirteitä: tuen saajat on valikoitava innovaatiokapasiteetin tapauskohtaisen arvioinnin perusteella eikä tukien kohdentamista voida toteuttaa yleisillä verotuksessa käytettävissä olevilla tiedoilla.

Perusotoksessa olivat kaikki suomalaiset innovatiiviset, vähintään kaksi henkilöä työllistävät yritykset. Tulokset osoittavat yritysten innovaatiokyvykkyyden mukaan kohdentuvan valikoivan innovaatiopolitiikan hyödyt. Mikäli tuet kohdennettaisiin ja mitoitettaisiin optimaalisesti, täysin yritysten t&k-toiminnan tuottavuuden perusteella, hyvinvointi kasvaisi nykykulutuksella mitattuna 3.7%. Käytännössä tähän ei päästä, mutta myös valikoimaton, optimaalisesti mitoitettu t&k-tuki vakiintuneille yrityksille tuottaa huomattavan hyvinvoinnin kasvun verrattuna nykytilaan. Noin 1.8% kasvuun hyvinvoinnissa päästäisiin hyvinvoinnin kasvun kannalta optimaalisesti mitoitetulla, valikoimattomasti jaetulla lisätuella, jonka suuruus olisi 3.9% innovatiivisten yritysten tuotannon arvosta. Tähän arvioon liittyy epävarmuutta, mutta se on samaa kokoluokkaa Acemoglun ym. (2018) löydösten kanssa. Koko Suomen talouden tasolla tämä tarkoittaisi t&k-tukien lisäämistä noin 1.1% bruttokansantuotteesta.

Suomalaisen rekisteriaineiston avulla pystyimme laajentamaan Acemoglun ym. (2018) aineistoanalyysia aivan pienimpiin yrityksiin. Innovaatiopolitiikan mahdollisuudet hyvinvoinnin lisäämiseen jäävät pienemmiksi 2-5 henkilöä työllistävien mikroyritysten ollessa mukana analyysissa. Tämä johtuu siitä, että mikroyritysten innovaatiopotentiaali ja toiminnan kiinteät kustannukset ovat pienempiä. Siten politiikan aiheuttama luova tuho ja työvoiman uudelleenallokointi yritysten välillä jää mittakaavalta pienemmäksi. Kun mukaan luetaan mikroyritykset, luovan tuhon hyödyt ovat hieman pienemmät kuin Yhdysvalloissa. Vähintään viisi henkilöä työllistävien yritysten joukossa politiikan hyödyt ovat suuremmat kuin Yhdysvalloissa.

Lisäksi tarkastelimme mallissamme korkeasti koulutetun työvoiman tarjontaan vaikuttavia tekijöitä. Havaitsimme, että politiikkamuutosten vaikutukset olivat suurempia, kun korkeasti koulutetut työntekijät määriteltiin kapeasti. Tämä johtui politiikan aiheuttaman työvoiman uudelleenallokaation merkityksen lisääntymisestä; kun korkean osaamisen työvoiman saatavuus on niukkaa, on kilpailu tästä avainresurssista voimakkaampaa toisaalta t&k-toimintojen ja muiden korkeaa osaamista edellyttävien toimintojen välillä ja toisaalta matalan ja korkean innovaatiokapasiteetin omaavien yritysten välillä. Tällöin politiikkatoimilla on tärkeämpi rooli yhteiskunnan kannalta optimaalisen t&k-työvoiman määrään toteutumisessa korkean innovaatiokapasiteetin yrityksissä. Tutkimme myös osaavan työvoiman tarjonnan lisääntymisen vaikutuksia, joka voi seurata esimerkiksi maahanmuuton myötä. Tarjonnan kasvulla on positiivisia vaikutuksia talouskasvuun, mutta niitä pitäisi toteuttaa yhdessä innovaatiopolitiikan uudistuksien kanssa.

Mitä paremmin tuet saadaan kohdennettua korkean innovaatiokapasiteetin yrityksiin, sitä suuremmat ovat positiiviset ulkoisvaikutukset. Tämä on seurausta siitä, että tämän päivän innovaatiot rakentuvat aiemmin tuotetun tiedon varaan; yritykset hyötyvät muiden yritysten aiemmin tuottamasta tiedosta innovaatiohankkeita toteuttaessaan. Yrityksen on esimerkiksi helpompi kehittää uusia hyödykkeitä, kun se voi oppia muiden yritysten markkinoille tuomissa tuotteissa käytetyistä ratkaisuista ja hyödyntää niitä. Yritykset hyötyvät myös muiden yritysten kehittämästä tietopääomasta, josta osa on julkisesti saatavilla (mm. patenttidokumentit ja kilpailijoiden tuotteiden sisältämät teknologiat). Erityisesti tilanteessa, jossa tuet voitaisiin täysin kohdistaa t&k-toiminnan tuottavuuden perusteella, tukien vaikutus on merkittävästi yksinkertaista tukea suurempi. Joka tapauksessa vaikutus on myönteinen vain, jos tuet eivät kohdistu merkittävällä tavalla markkinoilta poistuvien yrityksien toiminnan ylläpitämiseen.

Käytännössä tehokkaimmillaan innovaatiopolitiikan harjoittaminen vaatisi sitä, että t&k-tukipäätöksiä tekevien virkailijoiden pitäisi pystyä erottamaan toisistaan korkean ja matalan t&k-tuottavuuden yritykset. AAABK-tutkimuksessa korkean t&k-tuottavuuden yrityksille on ominaista matalan t&k-tuottavuuden yrityksiä suurempi innovaatiokapasiteetti. Suuremman innovaatiokapasiteetin yritykset onnistuvat todennäköisemmin lisäämään uusia, markkinoilla menestyviä tuotteita portfolioonsa. Käytännössä yritysten innovaatiokapasiteettia arvioitaessa uusien tuotteiden määrä tietyltä ajanjaksolta voisi olla yksi indikaattoreista. Innovaatiokapasiteetin määritelmää olisi kuitenkin tarkennettava niin, että siinä otetaan huomioon yritysten innovaatiokapasiteetti laajemminkin, esimerkiksi sellaisten innovaatioiden osalta, jotka parantavat laatua tai eivät ainakaan heti materialisoidu uusina tuotteina, sekä myös arviointi tulevasta innovaatiokyvykkyydestä ja innovaatioiden laadusta. Jälkimmäinen korostuu erityisesti tuottavuuskasvun kannalta keskeisten aloittavien ja nuorten innovatiivisten yritysten kohdalla. Niillä ei ole vielä pitkää historiaa, josta innovaatiokyvykkyyttä voitaisiin arvioida. Yritykset voivat myös elinkaarensa aikana vahvistaa innovaatiokapasiteettiaan, muun muassa tuotekehittäjien onnistuneilla rekrytoinneilla, jonka seurauksena innovaatiokyvykkyyden arviointi aiemman menestyksen perusteella ei ole täysin riittävää tuen optimaalisen kohdentamisen näkökulmasta.

Aiempi tutkimus tarjoaa näyttöä siitä, että Suomessa t&k-tuet ovat heikentäneet yritysten tuottavuuden ja markkinoilta poistumisen suhdetta ja mahdollisesti haitanneet resurssien uudelleenkohdentumista korkean tuottavuuden yrityksiin. Kosken ja Pajarisen (2015) tutkimus osoittaa, että t&k-tuet ovat vähentäneet tehottomien yritysten poistumista markkinoilta ja hidastaneet rakennemuutosta.

Taloustieteellinen kirjallisuus tarjoaa muitakin työkaluja, jotka voisivat auttaa päätöksentekijöitä kohdentamaan t&k-tuet aiempaa tehokkaammin kasvun edistämiseksi. Ns. ”kuoleman varjo” -ilmiötä tutkivat aineistoanalyysit viittaavat siihen, että markkinoilta poistuvien yritysten tuottavuudella on taipumus laskea huomattavasti jatkaviin yrityksiin verrattuna jo useita vuosia ennen kuin yritys poistuu markkinoilta (kts. esim. Almus, 2004; Carreira ja Teixeira, 2011). Tällaista aineistoanalyysiä voitaisiin käyttää markkinoilta todennäköisesti pian poistuvien yritysten havaitsemiseksi, ja kohdentaa t&k-tuki vain sellaisille vakiintuneille toimijoille, joiden tuottavuuskehitys ei indikoi markkinoilta poistumista. Menetelmää ei kuitenkaan voida käyttää verrattain nuorten yritysten elinkelpoisuuden arviointiin. On myös tärkeää huomioida, että vahvassa tuotekehitysvaiheessa olevien (erityisesti pienten) yritysten tuottavuus saattaa notkahtaa väliaikaisesti, kun uusia arvonlisää tuottavia palveluita tai tavaroita ei ole vielä markkinoilla.

AAABK-malli mahdollistaa kuitenkin vain melko yleisten yrityksiin tuottavuustason tai panostyypin mukaan kohdentuvien politiikkakeinojen vaikuttavuuden tarkastelun. Tämän takia mallikehikon tarjoamat mahdollisuudet arvioida Suomessa yleisesti käytettyjen hanketasolla kohdennettujen t&k-tukien optimaalisuutta ovat rajalliset. Tämä seuraa erityisesti siitä, että hanketason t&k-tukiohjelmissa optimaalisen tukien kohdennuksen tulisi ottaa huomioon myös moraalikadosta (moral hazard) ja haitallisesta valikoitumisesta (adverse selection) johtuvat tehottomuudet (Lach et al., 2021).

1 Introduction

Understanding the aggregate economic impacts of business subsidies is essential for planning and implementing an efficient innovation policy. In addition to the direct effects, the aggregate economic effects include the indirect effects of the policies on other companies through spillover mechanisms (e.g. knowledge spillovers) and market prices (e.g. labour costs). A successful subsidy policy may accelerate economic growth and improve competitiveness. On the other hand, sub-optimally allocated subsidies may slow down productivity growth in the worst case. Innovation policy is likely to strengthen productivity growth when subsidies are targeted at high-productivity companies, and they may instead have a detrimental effect on productivity when targeted at low-productivity companies.

The externalities related to knowledge spillovers that companies do not account for in their R&D investment decisions provide a primary rationale for public R&D subsidies. Microeconomic empirical studies assessing the direct effects of subsidies do not typically address the impacts of knowledge spillovers or the aggregate welfare effects of R&D subsidies.[1] In our analysis, spillovers emerge because a firm's R&D productivity is positively affected by the knowledge created by the past innovation efforts of other firms in the economy. This means that future innovations build on the existing knowledge stock. For example, creating a new product is easier when a firm observes existing products in the market that are produced by other firms, and making a technological innovation requires less research input when a firm can build on knowledge created by other companies (e.g. technological information documented in publicly available patent filings).

Our work applies the model developed by Acemoglu et al. (2018), henceforth *AAABK.* Central to the AAABK model is the ratio of high-productivity and low-productivity firms in total output and how different policy measures affect this relationship. In the model, the share of the skilled workforce allocated for research activities in companies with high R&D productivity is a key channel through which the government affects economy-wide productivity growth and welfare.

We replicate the analysis of AAABK by employing Finnish data and comparing the effectiveness of alternative policy measures with the actual policy implementation that was in place during the sample years. Our results for the Finnish economy are broadly in line with the US findings. In our baseline sample, which includes all Finnish

[1] However, a strand of microeconometric studies aims at estimating the magnitude of spillovers (Jaffe, Trajtenberg and Henderson, 1993; Bloom, Schankerman and Van Reenen, 2013; Dechezleprêtre et al., 2016).

innovative firms that have at least two employees, we find that there are clear benefits from a more active innovation policy that fosters creative destruction. For Finland, an optimal R&D policy that supports the innovative activities of companies that have high R&D productivity induces a 3.7% consumption equivalent welfare gain. With a general (non-targeted) R&D incentive, welfare gains are smaller but still positive (1.8%). These findings are, by and large, similar to qualitative conclusions on the effects of public policies on economic growth and welfare that are presented in the original work of Acemoglu et al. (2018) that used US data.

Acemoglu et al. (2018) employed US data from the 1980s and 1990s. We complement their work by estimating the AAABK model for more recent years: 2000–2016. Our results add to the literature by providing evidence on the aggregate effectiveness of innovation policies in this more recent period of slower economic growth. We also complement the literature by providing new perspectives with the help of the Finnish high-quality register data: our analysis employs comprehensive firm-level datasets and linked employer-employee datasets that cover the universe of active Finnish companies. We amend this data with an exhaustive, annual firm-level R&D investment panel, covering around 99% of gross R&D in the economy.

A key advantage of our dataset is that, unlike the data employed by AAABK, it also has good coverage of small companies. We analyse how the model responds to the inclusion of data concerning micro-sized firms that are not typically available in R&D datasets. Moreover, our dataset provides information on labour inputs at a very fine level. This allows us to measure R&D labour inputs and fixed operative labour inputs at the firm level and to construct measures for the skilled workers in the economy based on detailed occupation and educational degree categories. Furthermore, we provide results for some new policy applications of the AAABK model that can be particularly relevant for smaller economies, for instance, we provide an analysis of an immigration policy that increases the supply of skilled labour in the economy.

The effectiveness of business subsidies has previously been studied with Finnish data, mainly concerning their direct effects (see, e.g. Fornaro et al., 2020, for a literature review). Various micro-level studies employing data from different countries provide evidence on the direct impacts of R&D subsidies (see, e.g. Hyytinen and Toivanen, 2005; Koski and Pajarinen, 2013, 2015; Einiö, 2014; Bronzini and Iachini, 2014; Howell, 2017) or R&D tax incentives (e.g. Rao, 2016; Dechezleprêtre et al., 2016; Agrawal et al., 2020; Akcigit et al., 2021a) on companies' innovation activities and other economic performance measures, such as productivity. Studies providing the most reliable estimates of the causal impacts of these policies have utilised quasi-experimental settings in which the control group is plausibly similar to the subsidised firms in terms of observed and unobserved background characteristics. In such studies, the effects of support policies are estimated as the performance differences between these groups.

In recent years, macroeconomic analysis of the aggregate impacts of business support and, in particular, innovation policies, has expanded rapidly. The AAABK model employed in our study is one important recent contribution in this field. Another recent study by Ackigit et al. (2021b) emphasised the design of mechanisms for optimally allocating fiscal incentives for R&D. Their work analysed a realistic setting where the government does not have perfect information about the R&D effort of firms. They show that a Heathcote–Storesletten–Violante (HSV) type of subsidy combined with an HSV type of profit tax performs almost as well as the optimal policy. Atkenson and Burnstein (2019) constructed a simple first-order approximation of the impacts of a policy-induced change in innovation on aggregate productivity by employing a model that nests features from several canonical growth models. Takalo et al. (2017) built a structural model that allows for externalities, financial market imperfections and limited R&D participation. Their welfare analysis of R&D policies employed project-level data from Finland. Their findings indicate that R&D subsidy policies do not significantly improve welfare, although tax credits and subsidies increase R&D investments compared with laissez-faire markets without any R&D subsidies.

Our analysis is also related to work examining the consequences of other types of innovation policies. A recent study by Akcigit et al. (2018) built a general equilibrium framework of endogenous growth and trade for an open economy in order to evaluate the effectiveness of innovation and trade policies on economic growth and welfare. In their model, firms' motivation for innovation arises from defensive and expansionary strategies and domestic and international business-stealing effects. Their dynamic theoretical analysis indicates that reduced trade barriers increase innovation through stronger incentives for defensive and expansionary R&D due to increased foreign competition. Their data provide evidence that the introduction of R&D subsidies was an efficient innovation policy, restoring the competitiveness of US firms and creating positive longer-term welfare effects.

In the literature concerning the Finnish economy, a few studies have used a model-based approach (Maliranta and Määttänen, 2015) or productivity decomposition analysis (see, e.g. Hyytinen and Maliranta, 2013) to examine the reallocation of factors of production.

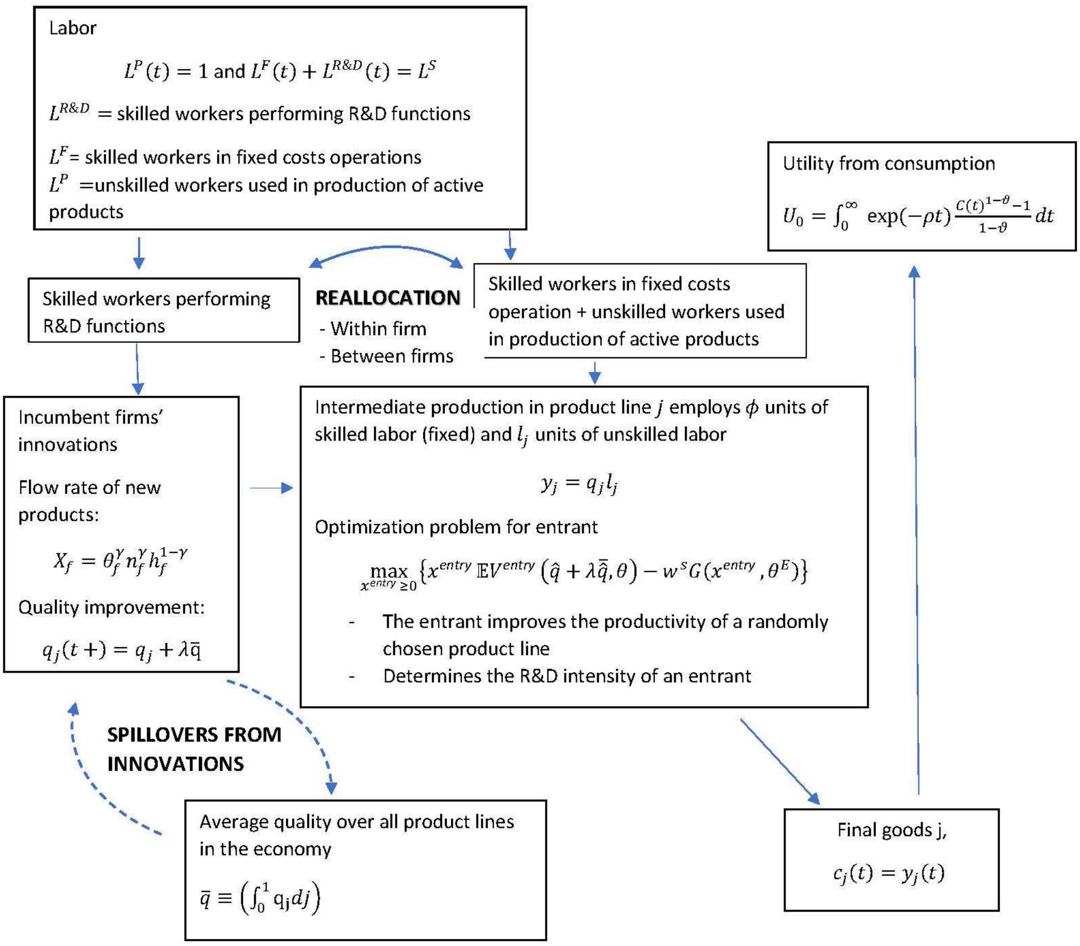
Our analysis is also linked to literature examining the relationship between creative destruction and economic growth. Garcia-Macia et al. (2019) argued that, for determining the welfare effects of innovation policies, it is essential to understand the extent to which growth is generated by creative destruction by entrants as opposed to the incumbents' improvements of their existing lines of business and new lines of business. They build a model in which aggregate productivity growth is generated via entrants' innovation and incumbents' improvements of their own products and innovation to generate products new to the firm that may either be 'stolen' from other companies or be new to the markets. Their data analysis indicates that incumbents' quality improvements of their own products form the most significant source of growth, while creative destruction accounts for a relatively low share of aggregate productivity growth.

The rest of the report is organised as follows. Section 2 presents the theoretical model. Section 3 first introduces the data used in the empirical analysis and then presents the estimation results concerning the parameters of the model. Section 4 reports the results for policy experiments based on the estimated model and further explores the impacts of various policy experiments on growth and welfare in the Finnish context. Section 5 provides some extensions to the analysis. Section 6 discusses the policy implications of our findings.

2 Theoretical model

In this section, we discuss the key equations and premises of the AAABK model that is then used to assess the effects of innovation subsides and taxes on the Finnish economic growth and welfare. Most of the analysis follows the structure presented in AAABK but we stress the model features that are important to our analysis. The model is characterised in Figure 2.1.

Figure 2.1. The model



The key market failure in the model is related to skilled labour. Because firms build on the quality level of existing leader firms, R&D creates positive spillovers onto other firms. However, firms do not internalise these spillover effects when considering their R&D effort. This implicates that there will be underinvestment in R&D and thus lower than the socially optimal demand for the skilled labour that is needed in the production of R&D.

Preferences and Final Good Technology

An important feature of the model is that there is insufficient R&D since firms do not internalise the full value of new innovations. This is typical in models of endogenous technological change. In this model, this feature is captured with future innovations building on the current knowledge stock, implying that current innovations create a positive spillover onto future innovators, as described in AAABK. The resulting underinvestment leads to the too little employment of skilled workers in R&D, on one hand, and, to too much employment in operations on the other hand.

The economy is in continuous time where a representative household has constant relative risk aversion (CRRA) preferences. The function describing household preferences can be found in Appendix 1.

The firms in the model economy have different product lines to choose from, and their outputs are then combined into an aggregate final good.

The idea of product lines is an important element in the model since it expresses firms as actors making decisions about retaining different product lines while allowing creative destruction at the product level at the same time. As a consequence, not all product lines are active at each point in time.

AAABK assumes that the model economy is closed. In this report, for reasons of keeping the model tractable and simple enough, we make the same assumption for Finland. This assumption is not as restrictive as it may first sound, even for a small open economy like that of Finland. Competition between domestic firms affects firms in a similar way to competition from abroad, that is to say, the basic mechanisms in both types of economies – open or closed – are the same.

The open economy aspect could still, of course, indirectly affect our results via general equilibrium effects. However, we abstract from the indirect effects in this report, which implies that innovation policies have no effects on the current account and foreign (direct) investments. In that sense, our model misses some aspects of the Finnish economy. Our aim is, however, to tackle these issues in future research; more specifically, our aim is to develop a model that contains these features of the Finnish economy as well.

R&D and production costs are understood in terms of labour, so $c_j(t) = y_j(t)$, where$y_j(t)$ is the amount of product *j* produced at time t. This implies that aggregate output equals aggregate consumption.

Following AAABK, there are two types of labour in the economy: skilled and unskilled labour. Unskilled workers are used in the production of the active products (total labour demand, L^P), while skilled workers perform R&D functions (total labour demand, $L^{R\&D}$) and are also employed in order to maintain the (fixed) costs of operations, such as management work, back-office function work and other non-production work (total labour demand, L^F). We assume that the operation of each product requires ϕ > 0 units of skilled labour.

Formally, the representative household has a fixed skilled labour supply of measure L^S and an unskilled labour supply of measure 1. Both groups' labour supply is inelastic. The labour market clears so that total labour demand equates labour supply for each type of labour, thus:

$$L^P(t) = 1 \text{ and } L^F(t) + L^{R\&D}(t) = L^S(t). \tag{1}$$

The representative household maximises its utility, subject to the budget constraint:

$$\dot{A}(t) + C(t) \leq r(t)A(t) + w^u(t) + L^S w^s(t). \tag{2}$$

Also, the no-Ponzi condition holds so we can write $\int_0^\infty exp(-r(t)t)A(t)dt \geq 0$, where $A(t)$ are the assets of the representative household, $r(t)$ is the equilibrium interest rate on assets, and $w^s(t)$ and $w^u(t)$ are skilled and unskilled wages, respectively. We follow AAABK and focus on stationary equilibria, which also allows us to drop the time subscripts when that is useful for characterisation.

Intermediate Good Production and Firms

The intermediate good (product) j is produced by the monopolist who has the leading-edge technology in that product line. The monopolist can own multiple product lines and can produce multiple intermediate goods simultaneously. There are two different sets of firms: (i) a set of active firms F that owns at least one product line and (ii) a set of potential entrants of measure one that do not currently own any product line but invest in R&D for innovation.

Following AAABK, let us denote by J_f the set of active product lines wherein firm f has the leading-edge technology and chooses to produce it, and n_f denotes the cardinality of this set. Firms have different innovative capacities. Upon successful entry into the economy, each firm draws its type $\theta \in \{\theta^h, \theta^l\}$, which corresponds to one of two possible types: high (*h*) and low (*l*) productivity. We write:

$$\Pr(\theta = \theta^h) = \alpha \text{ and } \Pr(\theta = \theta^l) = 1 - \alpha, \tag{3}$$

where $\alpha \in (0,1)$ and $\theta^h > \theta^l > 0$. It is also assumed that high-type firms transition to low-type at the exogenous flow rate $v > 0$. This transition effect is complemented with another exogenous shock: each firm is subject to an exogenous destructive shock at the rate φ. If a firm is hit by this shock, its value becomes 0 and it exits the economy.

Innovation by incumbents is approached as follows. Firm f of type θ_f hires h_f skilled workers for creating a new product, therefore adding one more product into its portfolio of products at the flow rate:

$$X_f = \theta_f^\gamma n_f^\gamma h_f^{1-\gamma}, \tag{4}$$

where $\gamma \in (0,1)$ and n_f is the number of product lines that firm f owns in total.

It is assumed that firms do not know ex ante in which particular product line they will innovate. As a result, their expected return to R&D is the expected value across all product lines: $j \in (0,1)$.

As a technical assumption, prices after entry are defined by Bertrand competition, implying that the more productive firm will be able to make any sales and profits, and thus only this firm will pay a (small) cost $\epsilon > 0$ and enter the market. Hence, in equilibrium, the firm that has the leading-edge technology can charge the monopoly price independently of the productivity gap between itself and the next best technology.

Entry and Exit

The firm with the leading-edge technology can act as a monopolist. Each entrant to the market has access to R&D technology $G(X^{entry}, \theta^E)$; it specifies the number of skilled workers necessary for generating at an innovation rate of $x^{entry} > 0$. Thus, an entrant aiming at achieving an innovation rate of x^{entry} would need to hire

$$h^{entry} = G\left(x^{entry}, \theta^E\right) \tag{5}$$

number of skilled workers. As explained in AAABK, this implies that a potential entrant has access to the same R&D technology that an incumbent with the innovative capacity θ^E and a single active product would have.

The optimisation problem for entrants can be stated as:

$$\max_{x^{entry} \geq 0} \left\{x^{entry}\, \mathbb{E}V^{entry}\left(\hat{q} + \lambda\bar{\hat{q}}, \theta\right) - w^s G\left(x^{entry}, \theta^E\right)\right\}. \tag{6}$$

Equation (6) implies that the entrant improves the productivity of a randomly chosen product line by $\overline{\lambda q}$, and at this point, the initial type of a firm, $\theta \in (\theta^h, \theta^l)$, is also realised.

The expected value of entry is $\mathbb{E}V^{entry}(.)$. Solving Equation (6) determines the R&D intensity of an entrant. Given that there is a unit measure of potential entrants, x^{entry} is equal to the total entry flow rate.

In the model, the exit of products and firms has three causes:

- (i) There is an exogenous destructive shock, given by $\varphi > 0$, which causes the firm to exit and shut down all its product lines.
- (ii) There is creative destruction because of innovation by other firms. This replaces the leading-edge technology in a particular product line.
- (iii) Firms voluntarily shut down some product lines because they are no longer profitable enough in regard to the fixed cost of operation.

As a consequence of the first and third factors, the measure of inactive product lines will be positive.

Value Functions

All the growing variables are normalised with a productivity index in order to keep the stationary equilibrium values constant. The average creative destruction rate is endogenously determined in equilibrium, in contrast with, for instance, the exogenous destructive shock defined earlier. The stationary equilibrium value functions for both low-type and high-type firms can be found in Appendix 1.

Aggregate Growth and Welfare

Aggregate output is equal to the productivity index, hence we can write $C = Y = Q$, where Q is the productivity index of the economy. Economic growth is linked to the frequency and size of innovations. One of the key advantages of using this kind of model is that it allows us to analyse the dynamic effects of innovation subsidies and taxes while also allowing heterogeneity between firms' innovation capabilities. It also enables a reasonable welfare analysis of different innovation policies that are chosen by the government.

When comparing the welfare in two economies with different policies (say, with Subsidy Policies 1 and 2) and the resulting growth rates (g(1) and g(2)) with initial consumption levels (C0(1) and C0(2)), consumption-equivalent changes in welfare need to be computed. This is done by calculating the fraction of initial consumption that will ensure the same discounted utility with the new growth rate as that gained with the initial allocation.

Solving the Model

The model is solved computationally as a fixed point of a vector of six aggregate equilibrium variables: the equilibrium skilled wage rate, the average innovation step size in relative productivity terms, the shares of product lines operated by high and low type firms, and the expected franchise values of upgraded product lines that is, a vector $(\tilde{w}^s, \Phi^h, \Phi^l, \bar{\hat{q}}, E[\Upsilon^h(\hat{q} + \lambda\bar{\hat{q}}), E[\Upsilon^l(\hat{q} + \lambda\bar{\hat{q}}))$, respectively. It turns out that the vector describes the equilibrium innovation decisions (the cost of innovation and its expected returns). In practice, the solution is obtained iteratively by using an initial conjecture vector and then updating the vector until the conjecture is verified following AAABK. This procedure yields us a fixed point and also generates the stationary equilibrium distributions of relative productivities.

3 Estimation

3.1 Data

The basis of our dataset is the Business Register (BR) compiled by Statistics Finland (SF). It covers all enterprises and corporations with value added tax liability or paid employees, except for very small companies with low labour input, turnover and total assets.[2] The key BR variable in our empirical analysis is turnover, for which the original source is the administrative tax registers. We next describe other key variables used in the empirical analysis.

Employment. We draw information on full-time equivalent employment from the BR. This variable is based on surveys conducted by SF. The surveys cover all multi-establishment firms with over five employees and single-establishment firms with over ten employees. In addition, a random sample of companies falling below these thresholds is surveyed. For companies that are not covered by these enquiries, full-time equivalent employment is estimated by SF using operating data and an industry code.

The number of individuals, counted by education and occupation. We calculate the annual firm-level number of personnel by employing the linked employer–employee data (i.e., the FLEED data) that provide employer company codes for each employee. We use the employer company code associated with the longest job spell of an employee in the last week of the year. These data cover the whole working-age population. To calculate the number of individuals according to their educational attainment and occupation, we use the FLEED code for the level of their highest degree (which has full coverage) and an occupation code (which covers employed individuals and is available for the year 2000 and the years 2004–2016). We aggregate the number of individuals in these categories by company and year. We define *highly educated individuals* as those who have university/college degrees and *non-production workers* as those who are managers, professionals, assistant professionals or technicians. The FLEED is also used to calculate the size of the workforce in managerial occupations or with a university/college degree in STEM (i.e.,

[2] The FRD sample frame excludes enterprises that (1) have been active for less than half a year, (2) have full-time equivalent employment below half worker years, (3) have balance sheet of less than 170 000 euros and (4) turnover below an annually specified limit (for example, below 11 016 euros in 2014).

science, technology, engineering and mathematics) fields. This measure mimics the AAABK definition of *skilled individuals in the economy*.

R&D expenditure and innovative status. Information on R&D expenditure is drawn from the annual R&D Survey (RDS) of SF. The RDS comprises a panel of R&D active firms who have reported R&D in the previous year's survey, have significant R&D expenditure in the previous year's SF Financial Statement survey or are recipients of public R&D funding. These firms cover around 99% of gross business R&D. Each year, the panel is refreshed with a survey of firms that are not included in it.[3] For firms with missing R&D values, we amend these data with predicted R&D expenditures based on annual patent counts and industry. This has little impact on the number of firms with positive R&D, which was expected due to the high private R&D sector coverage of the RDS. In our baseline specification, we follow AAABK and define a firm to be *innovative* in year t if it has positive R&D expenditure or a positive patent count in any year within a five-year window (that is, from $t-2$ to $t+2$).

Operative status and exit. We define a firm to be *operative* if it has positive BR turnover, positive BR employment or positive FLEED employment (for operative status, we examine both whether the firm has any employees in the last week of the year and whether the longest job spell of a worker is associated with the firm). A firm is defined as having *exited* in its last operative year (we restrict the analysis window so that operative status is observed one year after its end).

The fixed-labour-to-R&D-labour ratio. We calculate the ratio between fixed (operative) labour and R&D labour by combining information on worker-level occupational and educational categories at a fine level from the linked employer–employee data, aggregated by firm, and from firm-level information on the number of R&D workers counted by educational attainment from the RDS. In our primary specification, the ratio is the number of managers divided by the number of highly educated R&D workers. We also experiment with other combinations of the *operative worker* and *R&D worker* definitions, including wider *non-production worker* categories, *highly educated STEM workers* and *all R&D workers*. These alternative specifications yield

[3] Of enterprises that are not in the baseline RDS panel frame, the survey covers: (1) all enterprises with more than 100 employees, (2) a stratified random sample organised by industry and the size of enterprises that have 10–99 employees and (3) for enterprises with fewer than 10 employees, companies that have received public R&D funding in previous years. SF imputes missing responses based on the previous year's responses when the enterprise's R&D expenditure has been at least 170 000 euros. For these companies, partial non-responses are imputed by employing the ratio of the sum of the operating expenditure and the sum of salary expenditure. In the most common case of a partial non-respondent, the company provides information on R&D salary expenses but not on operating expenses.

similar results to our preferred specification, although the policy impacts based on our preferred specification provide slightly smaller impact estimates related to innovation policies.

We follow AAABK and define *small firms* as those with less than 200 employees and *young firms* as those which are less than 10 years old. We define moments related to exit, growth and age-size distribution as *annual changes* in the panel. Turnover and R&D are deflated using the consumer price index.

Sample Selection

Our analysis includes the year 2000 through to the year 2016 for which the key variables are available. We follow AAABK and focus on operative manufacturing firms that are continuously innovative. A firm is defined to be *continuously innovative* in year t if it is observed to be innovative in that year and in year $t - 5$ or $t + 5$. In principle, we could base our definition of *continuously innovative firms* on a smaller or wider time window because we observe operating and R&D data annually.[4] In our baseline model, we employ a five-year interval in order to have comparable results with those reported by AAABK. We also provide results for an alternative definition based on a two-year interval and for all operative firms (including firms that are not innovative).

We provide results from different samples in which we vary factors that may affect our estimation. One open question is, 'How much emphasis should be given to very small firms in the sample?' In our baseline sample, we only leave out firms that employ one person.

We then provide alternatives in which we focus on firms that have at least five employees. Moreover, we change the definition criterion for small firms from 200 employees to 110 employees, which provides a more balanced distribution of small and large firms in the Finnish dataset. We also examine the robustness of our analysis when we weight moments by firm employment. Overall, these alternative specifications provide broadly similar conclusions, although there are some differences that we discuss in more detail below.

[4] Operating data in AAABK is from a survey that is conducted every five years which dictates their choice of the time interval.

3.2 Estimation

The model is estimated with information on the underlying key characteristics of the economy. In particular, the procedure yields estimates of a set of underlying parameters for the model that are key factors in determining the dynamics of the model.

Fixed and Estimated Parameters

Similar to the work of Acemoglu et al. (2018), we take as a given some key underlying parameters. As standard choices in the literature and similar to the work of Acemoglu (2018), we choose the discount rate of $\rho = 2$ percent and the inverse of the intertemporal elasticity of substitution to be $\vartheta = 2$. The intertemporal substitution elasticity is the same as that used for Finland by, for example, Gorodnichenko et al. (2012). The discount factor, circa 97 percent at an annual rate, also corresponds well with the Finnish case as, typically, the discount factor in the Finnish quarterly models is 0.99. Similarly, we pick a standard value for the elasticity of substitution between different products to be 2.9. Following microeconometric innovation literature, we choose the elasticity of successful innovation with respect to R&D γ to be 0.5 (Blundell, Griffith and Windmeijer, 2002; Hall and Ziedonis, 2001). Finally, we set the ratio of high-skilled workers to the total number of workers in the workforce in the economy to be 20.9%, which is the ratio of the number of workers who are in managerial occupations or hold a higher-education STEM degree to the number of workers in the economy, calculated from the linked employer–employee data that covers the whole working-age population.[5]

The remaining eight parameters are estimated with the simulated method of moments (SMM). We compute the model-implied moments from the model and compare them to the data-generated moments to minimise the differences between model moments and the data moments. Our minimisation problem is

$$min \sum_{i=1}^{18} \frac{|model(i) - data(i)|}{\frac{1}{2}|model(i)| + \frac{1}{2}|data(i)|}.$$

The SMM searches repeatedly across sets of parameter values (i) in the model until the model's moments are as close as possible to the empirical moments. In particular, 18 moments are measured from the model and compared with the empirical counterparts.

[5] We aggregate employment to firm level by employing the company code of the employer for the primary job spell of a worker in the last week of the year.

The moments are listed in Table 3.2.1. They describe firm entry (measured through employment shares), exit rates, size transition rates, employment and sales growth rates, and innovation intensities. These moments are selected because of their economic importance for the mechanisms of the model. In our estimations, we assign an equal weight for each variable, whereas Acemoglu (2018) overweighted the aggregate growth rate of the economy.

Model Fit

We estimate the model with different data samples. Next, we report the model fit for two main specifications, either for the lower limit of two employees (our benchmark) or for the alternative lower limit of five employees. The former sample yields results for a sample of almost all the relevant innovative firms, while the latter omits micro-sized firms.

The estimated moments can be found in Table 3.2.1. Moreover, the table also includes the baseline US estimates reported by Acemoglu et al. (2018). BOX 3.2.1 summarises the differences between the Finnish and the US matched moments.

BOX 3.2.1 DIFFERENCES IN THE MATCHED MOMENTS OF THE FINNISH BASELINE AND THE US (AAABK) DATA

In this text box, we compare the empirical moments in the Finnish benchmark data and in the US (AAABK) sample. The moments can also be found in Table 3.2.1.

The Finnish and US moments could be different for three main reasons. First, AAABK use data that spans from 1987 through to 1997 while our analysis employs data from more recent years: 2000–2016. One important difference between these periods is that the economic growth is slower in the latter. Therefore, it could be expected that the Finnish moments reflect the slower overall growth rate. Second, our data has better coverage of small companies and therefore their fraction in the sample is larger for Finland. Overall, Finnish companies can be expected to be smaller on average, which further reduces the fraction of large companies in our data. Third, our R&D investment data includes information for medium-sized and small companies, while the US R&D data cover companies investing at least USD 5 million in R&D.

Our data shows that the transition rate of firms from large to small is quite large in the Finnish data, roughly 8.0% (vs 2.1% in AAABK), which may reflect a relatively weak growth period of the economy in the estimation sample. Meanwhile, the transition rate from small to large firms is lower at 0.8% (vs 3.8% in AAABK).

The probability of firms being *small* at the five-year periods, conditional on entry, is larger than the AAABK reference value (86.3% vs 75.3%). The share of entrants in the five-year period is smaller in the Finnish benchmark at 17.0% (vs 39.3% in AAABK).

The aggregate growth rate of the economy is substantially lower in the Finnish data, being 1.6% at an annual rate (vs 2.2% in AAABK). In particular, this is likely to reflect differences in the sample periods, with the Finnish sample incorporating the post-2008 stagnation. On the other hand, the average exit rates are similar in Finland, being 10.7% for small and young firms, 9.2% for small and old firms and 5.3% for large and old firms (vs 10.7%, 7.7% and 3.6% in AAABK, respectively).

Typically, smaller firms in Finland have been more active in terms of R&D relative to the US, whereas the old firms are less active. These differences could also result from better coverage of small innovative firms in the Finnish data. Sales and employment growth have been broadly weaker in Finland. The average sales growth has been 8.9% for small and young firms, 1.0% for small and old firms and -1.7% for large and old firms (vs 10.7%, 2.4% and -0.3% in AAABK, respectively). The average employment growth rates have been 5.4% for small and young firms, 0% for small and old firms and -2.8% for large and old firms (vs 10.6%, 3.5% and -0.5% in AAABK, respectively).

Overall, we find that the model fits the Finnish data relatively well, although the average deviation of the parameters is moderately larger than in the US data. This can be observed from the total score that measures the average percentual deviation of the model moments from the empirical moments.

This is partly because the estimation interval may not fully reflect stationary, long-term equilibrium. Rather, the moments reflect transitionary dynamics that our model is not equipped to incorporate. For example, the rate of transition from a large firm to a small firm has been somewhat higher than the rate of transition from a small firm to a large firm. On the other hand, this also reflects sample choices. We find that for the sample that omits the smallest firms, the overall fit of the model is better. This also holds true when the empirical moments are weighted by the numbers of employees, which also leads our empirical moments to emphasise larger firms (this is not reported in the table).

The different samples provide a rather similar fit to the data. The models incorporate the slow aggregate growth rate of the economy during the time period, only reaching the average annual rate of roughly 1.5%. This is a considerably slower pace than in the US estimations reported by Acemoglu et al. (2018).

We measure firm-level dynamics with a five-year interval in the data and in the model in order to maintain comparability between our model and the work of Acemoglu et al.

(2018). The five-year entrant shares of Finnish firms are somewhat lower than in the US, whereas the probability of remaining a small firm is higher. Firm exit rates on a five-year interval and R&D-to-sales ratios are similar to those reported for the US. On the other hand, the lower sales growth figures in Finland, when compared with the US, align well with the low Finnish aggregate growth rate of the economy.

In the Finnish case, young and small firms tend to grow faster and engage in more R&D activities than their older counterparts. However, they also have a higher exit rate from the market, implying that there are large risks involved in their operations.

It is notable that our benchmark model moderately underestimates the exit rates in the empirical moment. This may result in exaggerating the importance of policies that build on fostering higher creative destruction rates. On the other hand, the R&D efforts of young and small firms are underestimated, which probably leads to a bias in the opposite direction.

It is also worth pointing out that the fixed costs of operations relative to R&D are consistently estimated to be higher than in the data, taking the model closer to the work of Acemoglu et al. (2018). In this respect, it seems that finding a balance with other data moments necessitates a higher cost of operations in the model. Note that in our baseline, we use a definition of the empirical, fixed-cost moment that is somewhat different than that used in AAABK. However, we also try an alternative definition of the fixed costs that is closer to that of Acemoglu et al. (2018). Whereas in the baseline we measure the fixed-cost-to-R&D-labour ratio by using the share of managers and STEM highly educated workers to all R&D workers, we consider an alternative, wherein the measure is the ratio of all non-production workers to all R&D workers. While it yields a higher empirical data moment, perhaps surprisingly, we find that the use of a substantially higher empirical moment for the fixed-cost-to-R&D ratio still produces a quite similar moment in the model. This finding suggests that the empirical moment is not influential in our estimations.

All in all, while the model fit is not perfect, there are no clear indications that the deviations in the fit would bias our policy analysis.[6] In any case, we use a wide range of alternative samples, variable definitions and model specifications to analyse the robustness of our findings.

[6] We also investigate model fit in terms of non-targeted moments in our benchmark sample. We find that employment growth at the bottom-90 decile is -0.6% vs. -1.2% in the Finnish data, while at the top-10 decile the corresponding numbers are 1.8% vs. -0.6% in the data. In terms of the R&D to sales ratios, the corresponding numbers are 0.054 vs. 0.0467 and 0.074 vs. 0.1037, respectively.

Table 3.2.1. Matched and estimated moments in Finland and a comparison with AAABK.

	1: lower employment bound at 2			5: lower employment bound at 5			AAABK: Acemoglu et al. (2018)	
	Finland, model	Finnish data		Finland, model	Finnish data		US, baseline model	US, data
Description		**Est.**	**N**		**Est.**	**N**		
Transition from large to small firm	**0.028**	0.077	3148	**0.028**	0.074	3138	**0.021**	0.010
Transition from small to large firm	**0.033**	0.008	19648	**0.032**	0.009	17819	**0.038**	0.014
Probability of being a small firm (conditional on entry)	**0.871**	0.863	25352	**0.839**	0.852	23423	**0.848**	0.753
Five-year entrant share	**0.226**	0.170	13685	**0.236**	0.173	12627	**0.336**	0.393
Aggregate growth	**0.016**	0.016	25769	**0.017**	0.016	23851	**0.023**	0.022
Firm exit (of a small-young firm)	**0.076**	0.107	6034	**0.077**	0.103	5112	**0.097**	0.107
Firm exit (of a small-old firm)	**0.071**	0.092	14954	**0.073**	0.097	14030	**0.092**	0.077
Firm exit (of a large-old firm)	**0.016**	0.053	2262	**0.018**	0.056	2261	**0.036**	0.036
R&D to sales (of a small-young firm)	**0.094**	0.150	1406	**0.080**	0.081	1236	**0.086**	0.064
R&D to sales (of a small-old firm)	**0.057**	0.057	4615	**0.047**	0.049	4414	**0.066**	0.059

R&D to sales (of a large-old firm)	**0.052**	0.030	1323	**0.043**	0.030	1322	**0.059**	0.037
Sales growth (of a small-young firm)	**0.077**	0.089	6049	**0.068**	0.069	5143	**0.101**	0.107
Sales growth (of a small-old firm)	**0.012**	0.010	13617	**0.012**	0.013	12694	**0.040**	0.024
Sales growth (of a large-old firm)	**-0.027**	-0.017	2140	**-0.026**	-0.015	2134	**-0.005**	-0.003
Employment growth (of a small-young firm)	**0.073**	0.054	5847	**0.064**	0.045	4961	**0.101**	0.106
Employment growth (of a small-old firm)	**0.013**	0.000	12979	**0.014**	0.003	12058	**0.040**	0.035
Employment growth (of a large-old firm)	**-0.026**	-0.028	2014	**-0.025**	-0.026	2008	**-0.005**	-0.005
Fixed cost - R&D labor ratio	**4.509**	3.310	11621	**5.561**	3.477	11040	**4.175**	5.035
Total score	**0.532**			**0.445**			**0.290**	

4 Results

4.1 Estimated Model Parameters

We next report the estimated model parameters in different sample specifications. We collect them in Table 4.1.1.

Table 4.1.1. The estimated model parameters, based on different samples, and comparison with AAABK.

Parameter	Parameter description	1: BASELINE, LOWER EMP., BOUND AT 2	2: 1, but higher fixed cost moment	3: 1, but the small-firm threshold is 110	4: 1, but employment-weighted moments	5: LOWER EMP., BOUND AT 5	Acemoglu et al. (2018), baseline	
lam	Innovation step size	0.115	0.116	0.109	0.163	0.153	0.132	Estimated
psi	Exogenous destruction rate	0.015	0.015	0.019	0.012	0.017	0.037	Estimated
nu	Transition rate from high-type to low-type	0.273	0.256	0.458	0.582	0.402	0.206	Estimated
alpha	Probability of being high-type entrant	0.989	0.967	0.982	0.912	0.974	0.926	Estimated
phi	Fixed cost of operation	0.259	0.256	0.249	0.387	0.391	0.216	Estimated

theta_l	Innovative capacity of low-type firms	0.742	0.739	0.795	0.609	0.731	1.391	Estimated
theta_h	Innovative capacity of high-type firms	1.154	1.127	1.484	1.427	1.301	1.751	Estimated
theta_e	Innovative capacity of entrants	0.010	0.010	0.011	0.006	0.009	0.024	Estimated
eps	Constant elasticity of substitution	2.900	2.900	2.900	2.900	2.900	2.900	Fixed
disc	Discount rate	0.020	0.020	0.020	0.020	0.020	0.020	Fixed
gamma	Innovation elasticity	0.500	0.500	0.500	0.500	0.500	0.500	Fixed
sigma	Inverse of the inter-temporal elasticity of substitution	2	2	2	2	2	2	Fixed
Ls	Share of high-skilled workers	0.209	0.209	0.209	0.2091	0.209	0.166	Fixed

Note: EMP. = employment

Across the board, our results indicate a strong pattern of negative selection, similar to that found by Acemoglu et al. (2018). While entrants have a large chance of being a high-type firm, incumbent firms are much more likely to be a high-type, when young (rather than later in their life cycle). That is, high-type firms face a high probability of transitioning to being a low-type. Moreover, high-type firms are, indeed, more innovative than low-type firms.

A closer inspection shows how these findings depend on the underlying data. As a baseline, we use a sample that includes almost all innovative firms, only excluding firms that have a single employee. Alternatively, we put more emphasis on larger firms, either by focusing on firms with more than four employees or weighting firms by their employment when measuring the empirical moments. Moreover, we alter the characteristics of the sample that includes small firms in many ways as a robustness check. Whereas in the baseline we measure the fixed-cost-to-R&D-labour ratio by using the share of managers and STEM highly educated workers to all R&D workers, we consider an alternative where we measure the share of all non-production workers to all R&D workers. As already discussed, this yields a higher empirical moment for the operation-to-R&D-cost ratio, but has little impact on the estimated model.

When considering the estimated model in more detail, we find that the average innovation step size is larger when more emphasis is put on larger firms. The destruction rates are fairly similar, but the transition rates from high types to low types is considerably smaller in the samples that emphasise larger firms. Consistently, the fixed costs are estimated to be larger in the samples that put more weight on larger firms.

While the innovative capacity of the high-types is larger in all cases, this feature is more pronounced in the larger-firm samples. We further investigate differences between the Finnish and the US estimated parameters in Box 4.1.1.

BOX 4.1.1. DIFFERENCES IN THE ESTIMATED UNDERLYING PARAMETERS BASED ON THE FINNISH AND THE US (AAABK) DATA

When compared with the US data in Table 4.1.1, we find that the baseline innovation step size is smaller than in AAABK. However, the innovation step size is estimated to be larger in Finland when samples that omit micro-sized firms or that weight larger firms are used.

The exogenous destruction rate of firms is estimated to be substantially lower in all estimations that use Finnish samples, suggesting that firms are almost half as likely to discontinue their operations due to exogenous shocks than in the US. On the other hand, the transition rates from high types to small types is higher in the Finnish samples, while the Finnish firms tend to be of high type more often at the beginning, but in practice, the innovative capacity of the US firms is higher for both high- and low-types of firms.

Finally, the operational costs are somewhat larger than in the US sample, and this feature is more pronounced in the samples that emphasise larger firms.

All in all, we find that there is likely to be a strong pattern of negative selection in both countries, while there are non-trivial differences in their underlying parameters.

We then construct bootstrap standard errors for the estimated parameters from the baseline sample that involves firms that have more than one employee. We construct robust standard errors, clustered by firm, by bootstrap with 100 replications wherein a sample draw in each replication is a bootstrap sample of firm clusters (that is, sampling whole firm histories) and use the calculated empirical moments to re-estimate the model for each draw.[7] We find that the standard errors are relatively small.

Finally, it is worth mentioning that our robustness analysis here does not take into account uncertainty regarding the structure of the model beyond its estimated parameters. Later in this paper, we also investigate whether modifications in the model structure (that is, the addition of adjustment costs and varying the number of different types of firms) affect our results. Without going deeper into our findings, we note that they are relatively robust to changes in the model structure, too.

[7] A one-by-one inclusion of the estimated parameters of the sample of estimated moments suggests that the standard error estimates converge within 100 draws at the relevant degree of precision. It is notable that in some cases the estimation algorithm did not find the best fit within a reasonable simulation time, in which case we discarded the results.

Table 4.1.2. Bootstrapped standard errors for the estimated parameters using the data that involves firms that have more than one employee.

Parameter	Parameter description	1: LOWER EMP., BOUND AT 2	Bootstrap estimate, mean	Bootstrap, estimated standard error
lam	Innovation step size	0.115	0.115	0.001
psi	Exogenous destruction rate	0.015	0.015	0.000
nu	Transition rate from high-type to low-type	0.273	0.281	0.004
alpha	Probability of being high-type entrant	0.989	0.980	0.007
phi	Fixed cost of operation	0.259	0.262	0.003
theta_l	Innovative capacity of low-type firms	0.742	0.752	0.006
theta_h	Innovative capacity of high-type firms	1.154	1.149	0.009
theta_e	Innovative capacity of entrants	0.010	0.010	0.000

4.2 Policy Experiments

Having estimated the model, we could study several policy experiments that provide counterfactuals to the baseline innovation policy. Our estimated baseline economy implicitly includes the existing policies in the estimation period as its market outcomes and firm policy decisions reflect the underlying system. Correspondingly, all policy experiments should be considered as changes to the current policy.

Following Acemoglu et al. (2018), we first analyse the implications of simple policy changes that involves merely illustrative changes to the levels of R&D subsidies and taxation of the incumbent firms.

We then introduce a social planner that decides the optimal level of creative destruction and innovation. The social planner knows the properties of individual firms (that is, whether they are of low or high quality) and sets customised limitations and support for firms based on their perceived quality.

However, it may be unrealistic to assume that such information regarding the quality of the firms is available. Whereas the economic outcomes of individual firms are perceivable, the role of chance and other unobservable factors may conceal a firm's underlying type. Therefore, as a third policy option, we consider policies that do not differentiate between firms based on their quality but rather place similar policies on firms based on observable characteristics, such as productivity or entry status.

We first consider these options in our baseline sample, which includes all firms with more than one employee. Table 4.2.1 collects our results for this sample. In the last subsection, we also discuss differences across samples.

Before going into the policy experiments, it is worth noticing that there are some differences between Finland and the US in the benchmark economy (Experiment i, Table 4.2.1). In Finland, the innovation rates of the low-type firms are markedly smaller (0.194 vs 0.259) and they hold more product lines (0.599 vs 0.550). The threshold survival productivity for low-type firms is similar to the US level, whereas high-type firms have smaller survival productivity (1.138).

These findings transform into both a lower share of skilled labour engaged in R&D and lower creative destruction rates in Finland. Qualitatively, these findings are shared in all models that are estimated with the Finnish data, irrespective of the used sample (see Table 4.2.4.1).

Finally, we note that we do not make welfare comparisons across the US and Finland but merely focus on differences across policies in the two countries. Thus, we set in each case the benchmark welfare as 1.

Table 4.2.1. Policy results in the baseline sample (2+ employee firms) and comparison with the US baseline found in the work of Acemoglu et al. (2018)

		Innovation rate (x)			The share of product lines operated (phi)		Threshold survival productivity for		R&D to skilled labour	Creative destruction rate (tau)	Aggregate growth rate	Welfare, bm = 1
		Entry	Low type	High type	Low type	High type	Low type	High type				
i. Benchmark	**Finland**	**0.003**	**0.194**	**0.387**	**0.599**	**0.058**	**1.461**	**1.138**	**0.186**	**0.142**	**1.63 %**	**1**
	US	0.005	0.259	0.381	0.550	0.063	1.473	1.303	0.199	0.172	2.26 %	1
ii. Incumbent R&D subsidy, 1% of GDP	**Finland**	**0.003**	**0.204**	**0.413**	**0.569**	**0.071**	**1.499**	**1.178**	**0.207**	**0.148**	**1.71 %**	**1.007**
	US	0.005	0.274	0.407	0.530	0.069	1.510	1.338	0.218	0.178	2.34 %	1.006
iii. Fixed-cost subsidy, 1% of GDP	**Finland**	**0.003**	**0.192**	**0.381**	**0.606**	**0.055**	**1.452**	**1.127**	**0.181**	**0.140**	**1.61 %**	**0.998**
	US	0.005	0.256	0.376	0.556	0.061	1.463	1.293	0.194	0.170	2.24 %	0.998
iv. Entry subsidy, 1% of GDP	**Finland**	**0.010**	**0.184**	**0.348**	**0.555**	**0.085**	**1.499**	**1.263**	**0.208**	**0.141**	**1.62 %**	**0.984**
	US	0.014	0.246	0.351	0.495	0.102	1.513	1.385	0.220	0.171	2.25 %	0.984

v. Social planner, full	**Finland**	**0.004**	**0.191**	**0.462**	**0.249**	**0.294**	**1.885**	**0.379**	**0.327**	**0.188**	**2.16 %**	**1.037**
	US	0.006	0.254	0.453	0.056	0.447	2.404	0.278	0.342	0.223	2.94 %	1.045
vi. Social planner, only productivity	**Finland**	**0.007**	**0.194**	**0.387**	**0.506**	**0.123**	**1.544**	**0.311**	**0.220**	**0.152**	**0.018**	**1.011**
	US	0.009	0.259	0.381	0.397	0.189	1.612	0.299	0.233	0.185	0.024	1.016
vii. Social planner, only innovation	**Finland**	**0.003**	**0.188**	**0.394**	**0.589**	**0.069**	**1.461**	**1.138**	**0.185**	**0.142**	**0.016**	**1.000**
	US	0.005	0.256	0.387	0.545	0.069	1.473	1.303	0.198	0.172	0.023	1.000
viii. Optimal incumbent policy	**Finland**	**0.002**	**0.227**	**0.467**	**0.491**	**0.105**	**1.602**	**1.310**	**0.261**	**0.163**	**0.019**	**1.015**
	US	0.004	0.307	0.465	0.477	0.087	1.601	1.428	0.264	0.191	0.025	1.012
ix. Optimal operating policy	**Finland**	**0.004**	**0.227**	**0.461**	**0.483**	**0.110**	**1.609**	**1.336**	**0.265**	**0.165**	**0.019**	**1.016**
	US	0.006	0.308	0.460	0.460	0.098	1.615	1.457	0.271	0.193	0.025	1.014
x. Optimal entrant policy	**Finland**	**0.004**	**0.193**	**0.381**	**0.593**	**0.063**	**1.464**	**1.156**	**0.187**	**0.142**	**0.016**	**1.000**
	US	0.006	0.257	0.377	0.543	0.070	1.476	1.314	0.200	0.172	0.023	1.000
xi. Optimal incu. and oper. policy	**Finland**	**0.004**	**0.227**	**0.461**	**0.483**	**0.110**	**1.609**	**1.335**	**0.265**	**0.165**	**0.019**	**1.016**
	US	0.006	0.307	0.459	0.459	0.099	1.615	1.458	0.271	0.193	0.025	1.014

4.2.1 Simple Policy Experiments

As a first take, we increase the R&D subsidies across all innovative firms by 1 percent of GDP.

As the current R&D subsidy level is smaller in Finland than in the US, we expect to see stronger implications of changes in the R&D subsidies in Finland. In the model, an increase of 1 percent of GDP in the subsidy translates into a 14.97 percent subsidy of R&D spending of the continuing firms.

In our model (and similar to the work of Acemoglu et al., 2018), this leads into an increase in the innovation rates of both the low- and high-type incumbents. The increase for the low types is 1 percentage point (pp), while for the high-types, the effect is 2.6 pp. While both innovation and growth are increased as a result, the impact is muted as the policy increases the creative destruction rate by 0.7 pp. The effect arises through an increase in the skilled wage, whereas, unlike in the work of Acemoglu (2018), the entry innovation rate does not fall.

When the incumbent R&D subsidy is increased, it leads to further creative destruction in the market. The policy puts pressure on the profitability of the weaker firms and drives them out of the market. Overall, the amount of active product lines falls by 2.6 percent. However, the decline concentrates on the low-type firms, while the share of product lines operated by the high-type firms increases by 1.3 pp.

Meanwhile, there is a modest reduction in the amount of skilled labour allocated to operations which raises the ratio of skilled labour employed in R&D by 2.1 pp. Similarly to the US results reported by Acemoglu et al. (2018), there is a modest increase in growth from 1.63 percent to 1.71 percent, and aggregate welfare goes up by 0.7 percent in consumption-equivalent terms. This is a marginally higher rate than that found in the US.

To further illustrate the implications of policy, we also analyse the effect of a subsidy on the fixed costs of operations. In the model, this is the most direct way to support the continuation of existing firms. In our model, a subsidy of 1% of GDP to the incumbent fixed costs translates into a 3.72% subsidy to the fixed costs of the operations of continuing firms.

In terms of practical implementation, this policy would involve lowering the taxation of skilled workers in management, back-office functions, and other nonproduction work.

It is notable that, while such a policy is easily implemented in our model, it would be harder to design in practice and does not exist in the current system.

Such a subsidy works against welfare and economic growth in the model, the effect arising from the less efficient allocation of high-skilled workers. The growth rate of the economy falls by 0.2 pp and welfare by 0.2 percent. Meanwhile, in equilibrium, there is an increase in the overall amount of active product lines of 0.6 percent. Given that there is limited number of skilled workers, this means that research resources are crowded out by the increase in the economy's aggregate operational costs. The share of skilled labour in R&D falls by 0.5 pp. Less innovation means less growth.

It also leads to the weaker selection of firms as the policy change predominately increases low-type firms' survival rates. That is, because the exit rate of low type firms through creative destruction is higher than that of the high types and weakening the creative destruction process will thus allocate fewer skilled labourers to high-type firms. Overall, the creative destruction rate falls by 0.2 pp while the share of active high-type firms falls by 0.4 pp.

We also consider the implications of an entry subsidy that is equivalent to 1 percent of GDP. In the model economy, this transforms into a policy that subsidises the entry costs at the rate 68.58%. As a result, we observe an increase of the innovation effort of entrants – it increases from 0.3 percent to 1 percent. However, there is a simultaneous decrease in the innovation rates of continuing firms, -1.0 and -3.9 pp for low- and high-types, respectively. There is an overall decline in the number of active product lines, while the share of product lines operated by the high-type firms moderately increases. All in all, the effect on economic growth is negligible while the aggregate welfare effect is negative, lowering consumption equivalent welfare by 1.6 percent.

4.2.2 Social Planner

We then turn to the results of the social planner optimal policy. In our modelling framework and under certain additional assumptions, the social planner policy provides us with an estimate of the largest gains achievable with an innovation policy in the model economy.

Similar to the work of Acemoglu et al. (2018), the social planner cannot directly make production decisions or set prices, and only allows control of the entry, exit and R&D margins of different firms. This simplification abstracts us from the analysis of monopoly distortions, per se, but allows simple quantification of the optimal policy. In optimum, the social planner chooses the same-per-product R&D for all high-type firms and also the same R&D for all low-type product lines. Then, we can represent the problem of the planner as choosing both type-specific R&D intensities and the threshold levels of surviving firm productivities in order to maximise the representative household welfare subject the skilled labour market-clearing condition.

Under these restrictions, the social planner problem yields us the maximum increase in social welfare in respect to the current R&D policy.

We find that in our baseline model of the Finnish economy, the gains from the optimal policy are of a similar magnitude as that found in the US. When we include all the firms that have more than two employees in the estimation, we find that the consumption-equivalent welfare gain is 3.7 percent relative to the baseline economy. In the US model, the corresponding gain is 4.5 percent.

There is a substantial increase in the share of high-type firms and their innovation activities when the economy switches to the optimal policy. The share of high-type firms increases from 5.8 percent to 29.4 percent. Their innovation rate increases from 38.7 percent to 46.2 percent. The exit threshold productivity of the high types declines considerably.

On the other hand, the underlying policy increases the exit threshold productivity of low type firms. Their share as operators of active product lines falls from 59.9 percent to 24.9 percent, while the innovation rate of the remaining firms remains similar to the benchmark.

Overall, this impact is quite similar to that found for the US, although in the US there is an even more dramatic decline in the share of low-type firms, driven by a stronger increase in the productivity threshold for the survival of smaller firms. In the US model, the creative destruction rate increases to 22.3 percent, whereas in the Finnish model it remains at 18.8 percent, albeit the level in Finland is also lower in the baseline.

The economic growth rate increases in Finland from 1.63 percent to 2.16 percent, whereas it increases in the US from 2.26% to 2.94%.

A further partition of the social planner policy into its components (only adjusting either the minimum survival productivity thresholds or the R&D intensities) shows that by far the largest effect is created through the adjustments of the productivity thresholds. This alone will create a shift in the active product lines that are to be operated by high-type firms, while the rate of economic growth increases from 1.63 percent to 1.8 percent.

4.2.3 More Realistic, Uniform Policies

While the social planner solution shows that there is potential for substantial gains in the adjustments to the innovation policy, the practical implementation of the optimal policy is difficult. The social planner can observe the types of individual firms, while in practice, tax designs or support-granting agencies are limited in making such a distinction. Therefore, it is also useful to assess optimal support rates for policies that uniformly affect low- and high-type firms. They may provide information on the lower bound of the (neutral) policy prospects, and they may also gain knowledge on the potential benefits of improved selection (the differences between uniform policies and selective, social planner policies).

Our policy options are again similar to those used by Acemoglu et al. (2018). We show that the optimal rate of an incumbent R&D subsidy alone would be 41.66 percent, amounting to 3.9 percent of the innovative economy production. This alone would result in a 1.46 percent increase in welfare, while the economic growth rate would increase moderately from 1.63% to 1.88%. The increase in the subsidy is moderately higher than in the US, where the optimal increase would account to 3.62 percent of the innovative economy production.

The mechanism is qualitatively very similar to the simple 1% increase in the subsidy discussed above.

In the case of operation costs, we find that the optimal policy is, in fact, a large operations tax. With an optimal tax rate of 74.82 percent (69.37 in the US case), amounting to 11.43% of GDP (10.78% in the US), we can again obtain a significant increase in growth rate and welfare. The growth rate increases to 1.89 percent and the consumption equivalent welfare by 1.58 percent. Here, the mechanism works in reverse when compared with the simple operation-cost subsidy. The tax drives up the fraction of product lines operated by high-type firms and drives less efficient firms from the market.

Finally, a policy where both operation taxes and incumbent R&D subsidies are optimally employed to maximise welfare shows, perhaps surprisingly, that there are not many complementarities in the policies as their combination yields almost the same welfare increase as separate policies. This is, again, consistent with the results reported by Acemoglu et al. (2018).

4.2.4 Policy Impacts in Different Samples

Finally, we note that there are some differences in the results when the underlying estimation data is changed. It seems that the inclusion of very small firms (2–4 employees) in the estimation data used in our baseline moderately weakens the implications of the policies. An important reason for this is that the sample with very small firms lowers the estimate of fixed costs, thus weakening the effects of an increase/decrease in the rate of creative destruction. Similarly, the use of an alternative limit for small firms (using 200 employees instead of 110 employees as the criterion for defining a small firm) decreases the role of creative destruction.

Table 4.2.4.1. The policy impacts in different samples

	Innovation rate (x)			The share of product lines operated (phi)		Threshold survival productivity for		R&D to skilled labour	Creative destruction rate (tau)	Aggregate growth rate	Welfare, bm = 1
Specification	**Entry**	**low type**	**high type**	**low type**	**high type**	**low type**	**high type**				
Benchmark estimates											
1: LOWER EMP., BOUND AT 2	0.003	0.194	0.387	0.599	0.058	1.461	1.138	0.186	0.142	1.63%	1
2: 1, but a higher fixed cost moment	0.003	0.193	0.377	0.600	0.063	1.450	1.141	0.188	0.143	1.66%	1
3: 1, but with the *small firm* threshold set at 110	0.004	0.204	0.503	0.648	0.029	1.418	0.876	0.192	0.151	1.64%	1
4: 1, but with employment-weighted moments	0.003	0.191	0.620	0.425	0.028	1.852	1.081	0.162	0.101	1.65%	1
5: LOWER EMP., BOUND AT 5	0.003	0.213	0.483	0.419	0.031	1.862	1.478	0.158	0.108	1.65%	1
Acemoglu et al. (2018), US baseline	0.005	0.259	0.381	0.550	0.063	1.473	1.303	0.199	0.172	2.26%	1

Social planner optimum											
1: LOWER EMP., BOUND AT 2	0.004	0.191	0.462	0.249	0.294	1.885	0.379	0.327	0.188	2.16%	1.037
2: 1, but a higher fixed cost moment	0.004	0.190	0.447	0.238	0.312	1.885	0.344	0.327	0.189	2.18%	1.037
3: 1, but with the *small firm* threshold set at 110	0.005	0.211	0.631	0.439	0.141	1.672	0.507	0.308	0.186	2.02%	1.020
4: 1, but with employment-weighted moments	0.003	0.186	0.750	0.133	0.190	2.685	0.375	0.402	0.170	2.78%	1.099
5: LOWER EMP., BOUND AT 5	0.004	0.204	0.589	0.032	0.294	3.343	0.386	0.391	0.183	2.81%	1.110
Acemoglu et al. (2018), US baseline	0.006	0.254	0.453	0.056	0.447	2.404	0.278	0.342	0.223	2.94%	1.045

On the other hand, when we employ samples where there is less focus on the micro-sized firms (5+ employee firms, using employment-weighted moments), we find that the potential gains are higher than in the US. When considering the growth potential through the transition from benchmark policy to the social optimum, we find that welfare can increase by circa 10 percent, and economic growth reaches circa 2.8 percent.

Our approach has been so far focused on innovative firms, but as Acemoglu et al. (2018) also pointed out, similar dynamics should be observed more broadly among firms that do not report R&D, but nevertheless engage in innovation activities in order to achieve dominating positions in product lines. Following their example, we re-estimated the model by only using data on all manufacturing firms and moments that do not characterise R&D activity, and then quantify the implications of policy changes. We find that the results remain relatively similar, with positive welfare effects resulting from a transition towards more active higher R&D policy support. The social planner optimum raises consumption equivalent welfare by 1.75% in this case, again accompanied by a substantial increase in the economic growth rate and the rate of creative destruction.

5 Extensions

5.1 Labour Market Frictions

So far, we have not explicitly discussed the role of labour market frictions. It is natural to expect that there are reallocation costs involved in the creative destruction process. In particular, in the current context, costs may be incurred in the reallocation of labour from the original firm operating a product line to the new one taking it over. The costs may involve, for example, training or administrative expenditures.

Following Acemoglu et al. (2018), we assume that hiring new workers entails training costs, and training each type of worker requires υ workers of the same type for training. As a result, when a new firm hires *l* new unskilled workers and ϕ skilled workers for operations, it incurs an additional cost of $\upsilon[\widetilde{w}^U l + \widetilde{w}^U \phi]$. No additional cost of the reallocation of R&D inputs is assumed. We augment the firm decision problem and the corresponding Bellman equation similarly to Acemoglu et al. (2018).

As the labour market frictions are potentially important in the Finnish context but there is no clear empirical guidance for their calibration, we estimate the cost parameter, υ, from the Finnish data. As a reference, Acemoglu et al. (2018) *calibrated* it to be equal to one month's salary, based on the job-market friction calibration of Bloom (2009).

We re-estimate the model with the baseline sample, including all innovative firms that have two or more employees, but this time we include the additional estimable parameter, υ. Our cost parameter estimate is, $\upsilon = 0.019$, which implies that the average reallocation cost is 22.6% of the monthly salary.[8] While the estimate is somewhat smaller than that used by Acemoglu et al. (2018), it is sufficient to considerably reduce the benefits of the modified policies. Due to the additional cost, the rate of creative destruction is smaller, and there are fewer low-type firms in the markets in the first place. Therefore, while the policy further emphasises the role of high-types, there is much less room for improvement.

Let us discuss these findings further. It is notable that the inclusion of the reallocation cost creates severe problems in the matching of the model to the data. Two matched moments – economic growth and the fixed-costs-to-R&D ratio, in particular – fall

[8] When we, instead, do not overweight the fixed cost moment during the estimation, similarly to our baseline estimations, the reallocation cost almost doubles, whereas the fixed-cost-to-R&D ratio in the model remains well below 2.

considerably. This implicates, for one thing, that our previous, rather high fixed cost moment may have partially reflected the omission of the transition costs. However, there is also a slowdown in the creative destruction rate of the economy, which shows up as a decline in the economic growth rate. This is because the reallocation cost reduces the innovation rates of both high- and low-type firms.

To avoid the large deviations of these model moments from the empirical ones, we have overweighted the growth rate and fixed cost moments five times more than other empirical moments in our results above. The overweighting brings the moments close to the empirical counterparts. However, the rate of creative destruction remains low, and to maintain a higher growth rate of the economy, almost all product lines are operated by high-type firms already in the baseline. As a result, the estimated model generates very similar R&D-to-sales ratios across firm age and size. This contradicts the corresponding empirical moments.

Overall, the estimation of the reallocation costs appears to somewhat overburden the identification of the model, resulting in the mixed success of matching relevant empirical moments.

Therefore, we also consider an alternative approach where we calibrate the reallocation cost while otherwise using the baseline model parameterisation. This provides us with a reasonable approximation of the impact of reallocation costs while otherwise keeping the structure of the economy fixed.

In this case, when we calibrate the moderate estimate of the reallocation costs from the estimation with the Finnish data above, we find that the effect of the reallocation cost on the potential of policy is, in fact, almost as large as in our baseline without the reallocation costs. When raised to the US calibration (one month's salary), the effect is similar to that reported by Acemoglu et al. (2018), roughly halving the effect of the optimal policy impact on welfare and economic growth.

All in all, we find that the reallocation costs are likely to somewhat decrease the potential of innovation policies to improve welfare. However, the benefits of a more efficient innovation policy still seem to remain clear. While the impact of the reallocation cost can be very large in cancelling out the effect of the policy according to our estimations of the whole economic model with reallocation costs, this result is plagued by difficulties in the identification of the full model with reallocation costs.

5.2 Changes in Labour Supply

In this subsection, we discuss how economic activity responds to changes in the labour supply under different policies.

In the current model, the role of high-skilled workers, in particular, is important given that the main focus of the model is on the (re)allocation of the high-skilled labour inputs to R&D activities. Changes in the share of the high-skilled and low-skilled populations has a non-trivial effect on economic growth. On the other hand, an increase in the overall size of the population does not change welfare in a per capita sense, that is, there is no overall population scale effect.[9]

To demonstrate the important role of high-skilled workers, we employ an exogenous increase in their population share of 1 pp while we maintain the other parameters of the model at their baseline values. Therefore, as we increase the number of high-skilled workers, we simultaneously keep the fundamentals of the economy the same as before and the new equilibrium reflects an adjustment to the increased labour supply.

As a result of the change in the workforce, there is a moderate increase of 0.11 percent in the economic growth rate when policies are not changed otherwise. The innovation rates of the high-type incumbents increase from 38.7 percent to 39.7 percent, while the innovation rates of the low-type firms also increase, but to a lesser degree (by only 0.3 pp). The number of all active product lines increases while the share of product lines operated by high-type firms only grows moderately. The share of high-skilled workers devoted to R&D increases from 18.6 percent to 19.4. percent, thus implying that one fifth of the increase in high-skilled workers end up conducting R&D. Meanwhile, the creative destruction rate increases moderately from 14.2% to 15.1%.

All in all, even with the baseline policies, the economic growth rate increases, but only to a small extent. This is in stark contrast with the socially optimal policy outcome. When the addition of high-skilled workers is combined with a transformation to the optimal policy, the economic growth rate increases to 2.25 percent, whereas a change in the ratio of high-skilled employment only increases the economic growth rate by 0.11 pp, and the combined policy impact amounts to 0.62 pp.

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[9] We continue to abstract from the small open economy aspects. That is, we maintain the assumption that the economy operates under balanced trade and that the policies do not affect the external competitiveness of the economy. Furthermore, we do not account for the scarcity of resources (such as primary products, land and capital) as a factor that could restrict the size of the economy. We acknowledge these factors may generate scale effects, but in the current context, their effects are likely to be secondary.

5.3 Three Types of Firm

As another robustness check, it is also worthwhile asking what implications would a model with three, rather than two, types of firm have for policy. Focusing only on a few firm types in order to characterise firm population is a necessary simplification, but an augmented model by Acemoglu et al. (2018) allows us to investigate the extent to which the results are sensitive to the number of firm types. We again use our baseline sample and this time estimate the model with three types of firm (low-, medium-, and high-productivity firms).

We find that the results remain quite similar. For example, a shift from the baseline to socially optimal policy results in a 3.17 percent increase in consumption-equivalent welfare, and the annual economic growth rate rises from 1.63 to 2.08 percent. Thus, it seems that our benchmark assumption that there are two firm types does not drive the results.

6 Conclusions

We replicate the empirical analysis of Acemoglu et al. (2018) and further estimated some extensions using the Finnish data for the years 2000–2016. Our empirical findings yield, by and large, similar qualitative conclusions on the effects of public policies on economic growth and welfare as those reported in the original work that used the US data.

Above all, the results emphasise the importance of reallocating skilled labour to its most productive use. When there is an underlying trade-off between using a skilled workforce in operative non-R&D tasks and R&D tasks that improve the productivity of the economy, policies that foster the reallocation of skilled labour to the R&D activities of the firms that are most productive in innovating can be highly beneficial. One important mechanism operates through the creative destruction of companies that have a low innovation capacity, as a result of which, a skilled workforce can be reallocated to firms with a high innovative capacity. A key lesson is that R&D policies should avoid allocating support in such a way that it prevents the destruction of less-productive technologies. When this is achieved, both R&D subsidies and/or tax-incentives can yield productivity and welfare gains.

In line with Acemoglu et al. (2018), we find that R&D support targeted uniformly to all companies, irrespective of their innovation capacity, is effective policy but not the most efficient. The underlying reason is that uniform subsidies do not achieve the optimal allocation of resources to the most efficient use and may even discourage innovation of continuing firms and entrants, and consequently restrain economic growth. This occurs because under uniform (untargeted) policies also low-R&D-productivity companies receive subsidies and remain in business, binding the R&D worker resource to innovative activities which have a lower likelihood to succeed.

Our baseline sample includes all Finnish, innovative firms that have at least two employees. We find that an optimal policy by a welfare-maximizing social planner increases aggregate welfare by 3.7 per cent in consumption equivalent terms. While an optimal policy which target firms with high innovative capacity may be hard to achieve in practice, even uniform incumbent R&D subsidy that does not distinguish between firm types can result in a welfare gain that accounts for around half of the social planner's gains. Our analysis indicates in order to reach the optimal level of a uniform R&D subsidy, R&D subsidies should increase by 3.9% of the innovative firms' aggregate turnover. As firms in our model economy account for around 29% of the overall economic activity in Finland, this increase corresponds to around 1.1% of GDP.[10]

While carefully targeted innovation policy was shown to be welfare-improving, it was also shown that some subsidies can be harmful. For example, the analysis showed that tax subsidies on operational costs of incumbent firms that divert high-skilled employees away from R&D activities had negative welfare effects. This type of policy corresponds to typical industrial policies that subsidize non-R&D operations of incumbent firms.[11] In fact, an optimal policy would be to tax such operational costs in combination with R&D subsidies rather than support them. However, implementation of such taxes on operational costs would be difficult in practice and the added gain from their use is moderate, and thus we argue that their practical value is limited.

While our results are broadly in line with the findings in Acemoglu et al. (2018), our analysis also provides some new insights that arise from the Finnish, high-quality register data. First, we analyzed how the model responded to the inclusion of micro-sized firms into the estimation sample, which is not examined by Acemoglu et al. (2018). We showed that when the smallest firms (2-5 persons) are included, innovation policy has a smaller potential to increase welfare. This is because the estimated model for the sample including micro-sized firms implies both that the innovation potential of individual firms and the fixed costs of operations are smaller. As a result, the policy-induced reallocation of labor across firms generates less creative destruction. In this sample, the benefits of creative destruction are moderately lower than estimated by Acemoglu et al. (2018). On the other hand, when we focused on firms with at least 5 employees, we found that the benefits of the policies were generally larger than for the U.S.[12] Second, Acemoglu et al. (2018) employ US data from the 1980s and 1990s. We complement their work by estimating the AAABK model for more recent years 2000-2016. Our results add to the literature by providing evidence on the aggregate effectiveness of innovation policies in this more recent period of slower economic growth.

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[10] We note that as our model is estimated for the innovative sector, our analysis does not account for the potential reallocation and general equilibrium effects that may result from the change in the innovation policy in the non-innovative sector and between sectors.

[11] Following AAABK, we consider subsidies or taxes on the fixed cost of operations rather than on all costs or on accounting profits. This is because taxes on accounting profits would also affect markups and partly eliminate the effects of the policies we are interested in. Subsidies or taxes on accounting profits of incumbent firms have, however, broadly similar impacts (Acemoglu et al., 2018).

[12] We obtain similar results when we include also micro-sized firms and estimate the model using employment-weighted moments.

We also examined the implications of how the calculation of high-skilled labor affects the results. We found that the effects of the policies were larger when high-skilled workers were more narrowly defined. Again, this arised from the resulting increase in the importance of policy-induced reallocation. We also studied the implications of an increase in the skilled-labor supply that may occur, for example, through immigration. We show that an increase in the supply has positive effects on economic growth.

In all cases, the optimal public policy forces low-productivity incumbents to exit and re-allocate their resources for more productive use in companies with higher innovative capacity. Such a productivity-enhancing selection of firms and reallocation of workforce can be achieved by targeting R&D subsidies in the case of incumbents primarily for companies with higher innovative capacity and reducing or not allocating subsidies to low-type incumbents. In practice, this would mean that the decision-makers allocating R&D subsidies would need to distinguish between firms with high and low innovation capacity. AAABK provide some guidelines for detecting high- and low-innovation-capacity companies. Higher innovative capacity companies tend to add more new products to their portfolio. In a practical evaluation of the firms’ innovation capacity, the number of new products of a specified number of past years could be one indicator. However, the definition of innovative capacity should be modified to consider further innovation that is merely quality enhancing or does not, at least not immediately, materialize as new products. The assessment of the innovative capacity of new firms and entrants, however, would require a more detailed analysis of the company’s R&D resources and strategy.

There is also prior empirical evidence that in Finland, materialized allocation of R&D subsidies has weakened the relationship between firm productivity and exit and potentially hindered the reallocation of resources to more efficient firms. The study by Koski and Pajarinen (2015) employing Finnish data shows that subsidized firms whose productivity is relatively low or has decreased are less likely to exit the market than they would be without subsidies.

Our analysis does not evaluate directly the impacts of policies related to climate policy. Our results do, however, provide some indirect insights on the consequences of such policies. If support is targeted to R&D projects that develop new knowledge relevant for green technologies, the support will to this extent also promote green transition. Quantitative analysis of such impacts is out of the scope of our paper, however.

Economic literature provides additional tools that might help policymakers target R&D subsidies more efficiently to promote growth. A stream of empirical studies suggests that a firm’s productivity level tends to decrease substantially, compared to continuing firms, several years before the firm exits the market (see, e.g., Almus, 2004; Carreira and Teixeira, 2011). This is the so-called “shadow of death”. This type of empirical analysis could be utilized to detect incumbent companies close to their exit margin and further allocate subsidies only to those incumbents that do not exhibit notably declining productivity levels during the past years. Consequently, inefficient subsidy allocation could be avoided or at least reduced by letting low-productivity companies exit the market and release their resources to more efficient use.

The AAABK model facilitates examination of fairly general policies that target companies by R&D-productivity level or inputs by type. It is therefore limited in assessing optimality of R&D support targeted at the project level, which is a commonly used innovation policy tool in Finland. In such programmes, optimal design should account for inefficiencies due to moral hazard and adverse selection (Lach et al., 2021).

Appendix 1.

Preferences and Final Good Technology
The economy is in continuous time where a representative household has the following constant relative risk aversion (CRRA) preferences:

$$U_0 = \int_0^{\infty} \exp(-\rho t) \frac{C(t)^{1-\vartheta} - 1}{1-\vartheta} dt, \tag{1}$$

where ρ > 0 represents the discount factor and *C(t)* represents a consumption aggregate that can described as:

$$C(t) = \left(\int_{\mathcal{N}(t)} c_j(t)^{\frac{\varepsilon-1}{\varepsilon}} dj \right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{2}$$

where *c* is the consumption of product *j* at time *t*, N(*t*) ⊂ [0, 1] is the set of active product lines at time t and ε > 1 is the elasticity of substitution between products.

Value Functions

All the growing variables need to be normalised by $Q(t)$ in order to keep the stationary equilibrium values constant. We follow Acemoglu et al. and denote the normalised value of a generic variable X by $\tilde{X}$. Then, τ denotes the average creative destruction rate. This is endogenously determined in equilibrium, in contrast with, for instance, the exogenous destructive shock defined earlier. The stationary equilibrium value function for a low-type firm can be written as:

$$\begin{aligned} &r\tilde{V}_l(\hat{Q}) \\ &= \max\left\{0, \max_{x \geq 0} \left[\Sigma_{\hat{q} \in \hat{Q}} \left[\tilde{\pi}(\hat{q}) - \tilde{w}^s \phi + \tau\left[\tilde{V}_l(\hat{Q} \setminus \{\hat{q}\}) - \tilde{V}_l(\hat{Q})\right] + \frac{\partial \tilde{V}_l(\hat{Q})}{\partial \hat{q}} \frac{\partial \hat{q}}{\partial w^u} \frac{\partial w^u}{\partial t} \right], \right.\right. \\ &\qquad \left.\left. -n\tilde{w}^s G(x, \theta^l) + nx\left[\mathbb{E}\tilde{V}_l(\hat{Q} \cup \{\hat{q} + \lambda\bar{\hat{q}}\}) - \tilde{V}_l(\hat{Q})\right] + \varphi\left[0 - \tilde{V}_l(\hat{Q})\right]\right]\right\} \end{aligned} \tag{3}$$

where $\hat{Q} \cup \{\hat{q}_{j'}\}$ is the new portfolio of the firm after successful innovation in product line j' while $\hat{Q} \backslash \{\hat{q}_j\}$ denotes the loss of a product with technology $\hat{q}_j$ from firm f's portfolio $\hat{Q}$ that is caused by creative destruction.

The value function in Equation (3) can be interpreted as follows. The left-hand side is the flow value of a low-type firm with a set of product lines given by $\hat{Q}$, given the discounting rate r. As is typical in these kinds of models, the right-hand side consists of the components that make up this flow value.

The first line (inside the summation) includes the instantaneous operating profits, subtracted by the fixed costs of operation, plus the change in firm value in the case when any of its products is replaced by another firm through creative destruction at the rate τ, plus the change in firm value. The latter is based on the increase in the economy-wide wage and accounts for the fact that, as the wage rate increases, the relative productivity of each of the products that the firm operates declines. Then, the first term in the second line depicts the R&D expenditure cost for firm f. The next term expresses the change in firm value when the low-type firm is successful with its R&D investment, materialising at the rate x. The last term captures the change in value when the firm exits due to an exogenous destructive shock, which the economy confronts at the rate φ.

Following the same logic as in Equation (3), the value function of a high-type firm can be written as:

$$
\begin{aligned}
& r\tilde{V}_h(\hat{Q}) \\
&= \max\Big\{0, \max_{x\geq 0}\Big[\textstyle\sum_{\hat{q}\in\hat{Q}}\Big[\tilde{\pi}(\hat{q}) - \widetilde{w}^s\phi + \tau\big[\tilde{V}_h(\hat{Q}\backslash\{\hat{q}\}) - \tilde{V}_h(\hat{Q})\big] + \frac{\partial\tilde{V}_h(\hat{Q})}{\partial\hat{q}}\frac{\partial\hat{q}}{\partial w^u}\frac{\partial w^u}{\partial t}\Big] \\
&\qquad\qquad -n\widetilde{w}^s G(x,\theta^h) + nx\big[\mathbb{E}\tilde{V}_h(\hat{Q}\cup\{\hat{q}+\lambda\bar{\hat{q}}\}) - \tilde{V}_h(\hat{Q})\big] \\
&\qquad\qquad\qquad +\varphi\big[0-\tilde{V}_h(\hat{Q})\big] + \nu\big[\tilde{V}_l(\hat{Q}) - \tilde{V}_h(\hat{Q})\big]\Big]\Big\}.
\end{aligned}
\tag{4}
$$

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