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Knowledge Diffusion, Endogenous Growth, and the Costs of Global Climate Policy

By Lucas Bretschger, Filippo Lechthaler, Sebastian Rausch, and Lin Zhang*

This paper examines the effects of knowledge diffusion on growth and the costs of climate policy. We develop a general equilibrium model with endogenous growth which represents knowledge diffusion between sectors and regions. Knowledge diffusion depends on accessibility and absorptive capacity which we estimate econometrically using patent and citation data. Knowledge diffusion leads to a "greening" of economies boosting productivity of "clean" carbon-extensive sectors. Knowledge diffusion lowers the costs of global climate policy by about 90% for emerging countries (China) and 20% for developed regions (Europe and USA), depending on the substitutability between different knowledge types. (JEL O33, O44, Q55, C68).

Knowledge capital accumulation and technology are important drivers for economic growth. In open economies, sharing knowledge—in contrast to acquiring rival factor inputs such as human and physical capital—provides an inexpensive way of fostering endogenous innovation (Eaton and Kortum, 1999; Keller, 2002). To the extent that knowledge diffusion enhances the productivity of "clean" carbon-extensive relative to "dirty" carbon-intensive inputs, it can also lower the costs of environmental regulation, in particular of policies that act on an international level, such as global carbon mitigation policies to combat climate change. Leading economic analyses have scrutinized the interactions between the environment, growth, and technology. For example, Nordhaus (1994) and Stokey (1998) show that growth can be limited by environmental constraints, while Aghion and Howitt (1998) and Acemoglu et al. (2012) demonstrate that sustainable growth is possible with climate policy that redirects innovation toward clean inputs. Also, firms may innovate more in clean technologies when they face a climate policy (Aghion et al., 2016; Calel and Dechezleprêtre, 2016). The role of knowledge diffusion for economic growth and for the costs of environmental regulation, however, has received surprisingly little attention.

This paper develops a multi-sector multi-region endogenous growth model to

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study the effects of knowledge accumulation and diffusion for growth and the costs of global climate policy. Following endogenous growth theory (Romer 1990, Aghion and Howitt 1992, Helpman 1992), knowledge, or technology, is non-rival in the sense that the marginal costs for an additional firm or individual to use the technology are negligible. In addition to knowledge spillovers among firms within a sector, we represent knowledge diffusion between sectors and regions. We distinguish between knowledge flows originating from a shared knowledge pool (Adam 1990; Stiglitz 1999) and their subsequent effects on knowledge creation reflecting the idea of accessibility and absorptive capacity of external knowledge (Lane and Lubatkin 1998; Haskel, Pereira and Slaughter 2007). Absorptive capacity positively depends on the existing stock of knowledge capital. As green sectors tend to be relatively capital-intensive, knowledge diffusion is higher among clean relative to dirty sectors—which is in line with recent empirical findings (Dechezleprêtre, Martin and Mohnen, 2014; Calel and Dechezleprêtre, 2016; Aghion et al., 2016).[1] These technology effects are included in a fully specified general equilibrium model which is (1) based on econometrically estimated knowledge diffusion processes using patent and citation data and (2) calibrated to sectoral production, consumption, and international trade patterns of four major world regions.[2]

Our model highlights *size effects* and *competition effects* through which knowledge diffusion affects growth and costs of climate policy. Size effects positively impact the productivity of firms which benefit from knowledge flows, hence lowering the production costs of production. Competition effects change the pattern of comparative advantage between sectors and regions to the extent that the accessibility and absorptive capacity of knowledge differs among firms, both across sectors and regions. While for a closed one-sector economy knowledge diffusion works solely through a size effect, the direction of the competition effect and relative magnitudes of both effects are a priori unclear in a multi-sector and multi-region general equilibrium framework. To the best of our knowledge, our paper is the first to develop a systematic framework for the analysis of domestic and international knowledge diffusion in a fully specified general equilibrium model with endogenous growth that permits investigating the costs of global climate policy.

Our analysis shows that knowledge diffusion, through both size and competition effects, leads to a "greening" of economies. Sectors with relatively low carbon intensities are characterized by high knowledge capital intensities, implying a large absorptive capacity. Knowledge diffusion thus boosts the productivity of these "clean" carbon-extensive sectors by more than it does for "dirty" carbon-intensive sectors. This, in turn, decreases the production costs of "clean" (non-energy) relative to "dirty" (energy) goods. When energy (carbon) inputs become more expensive under a climate policy regime, the costs of substituting away from carbon-intensive

[1] Dechezleprêtre, Martin and Mohnen (2014) find that clean patents receive on average 43% more citations than dirty patents and are also cited by more prominent patents. The reasons are that clean technologies have more general applications and that they are radically new compared to more incremental dirty innovation.

[2] We include China, Europe, USA, and an aggregate world region.

goods are hence lowered because "clean" goods can be produced at lower costs. This positive effect is re-enforced over time and across markets and space: "clean" sectors with higher productivity increase market shares in total output over time and benefit from increased competitiveness on domestic and international markets.

Notably, we find that the costs of a global climate policy, achieving a given (absolute) reduction of carbon dioxide (CO_2) emissions, can be substantially lowered through this "greening" effect arising from domestic and international knowledge diffusion. For regions with relatively little own knowledge (e.g., China), reductions can be up to 90%. For developed regions (e.g., Europe and the U.S.), policy costs can decrease but also increase depending on the strength of the "greening" effect. If the substitutability between different types of knowledge is high, costs are reduced by up to 20%. However, the costs of climate policy for these regions slightly increase when the substitutability is low. A simple but important implication of our analysis is, that in order to control emissions, carbon pricing policies should be complemented by R&D policies aimed at promoting knowledge diffusion. While this general insight is not novel (see, e.g., Acemoglu et al., 2012), we provide further support for this argument view by focusing on the effects from knowledge diffusion that could be created through R&D policy.

The impacts of knowledge spillovers on economic growth are substantial, corresponding to welfare gains for the global economy of about 4-10%; they depend on the substitutability between different types of knowledge. Regions with initially relatively low knowledge (e.g., China) benefit the most from knowledge diffusion whereas developed regions (e.g., Europe and U.S.) gain relatively less. In line with previous analyses (Eaton and Kortum, 1999; Keller, 2002), we find that the major sources of technical change leading to productivity growth are not domestic but, instead, lie abroad: international knowledge spillovers account for two thirds of the increase in knowledge capital due to knowledge diffusion, domestic spillovers contribute one third.

Our paper is related to the literature in several ways. We introduce knowledge spillovers between sectors and regions into the endogenous growth model (Romer 1990; Rebelo 1991; Aghion and Howitt 1992; Helpman 1992) in which profit-motivated industrial innovations in R&D *within a sector* lead to the accumulation of technological knowledge which is only partially excludable and non-rival, and hence, becomes a source of growth. Investigating knowledge diffusion in an endogenous growth model is important because gains from endogenous innovation are compounded to the extent that knowledge can be shared.

We focus on disembodied knowledge spillovers that represent technical change driven by the diffusion of knowledge accumulated in a shared knowledge pool.[3] The idea of "knowledge pools" as platforms for knowledge spillovers has been widely used in the literature. Adam (1990) posits the existence of "learning pools" for industries which consist of the findings from basic research. Similarly, Stiglitz (1999) argues

[3]Embodied spillovers, in contrast, represent technological change that is triggered by technological know-how embodied in foreign products or directly transferred innovations (patents).

that knowledge should be viewed as a global public good rather than as a public good whose accessibility is restricted by (geographical and political) boundaries. Through modern information technology, new knowledge can be easily diffused without being embodied in a particular product (Griliches, 1992).[4]

Building further on the knowledge diffusion literature, we adopt the concept of absorptive capacity which reflects a firm's ability to recognize the value of new information, assimilate it, and apply it to commercial ends (Cohen and Levinthal, 1989). We adopt the view that absorptive capacity of a sector positively depends on prior related own knowledge (Lane and Lubatkin 1998; Haskel, Pereira and Slaughter 2007; Mancusi 2008). The process of transforming the external inflow of knowledge from the knowledge pool into usable knowledge depends in our model on knowledge but also on the accessibility of knowledge sources, in turn reflecting geographical and technological barriers for diffusion. We further contribute by operationalizing these concepts in a fully specified general equilibrium model.

Our analysis is related to the empirical literature on estimating knowledge diffusion using "micro-data" on patents and citations at the technology and regional level and across time. Various channels for knowledge spillovers are emphasized in the literature. For instance, Coe and Helpman (1995), Coe, Helpman and Hoffmaister (1997), Keller (1998, 2004), and Lumenga-Neso, Olarreaga and Schiff (2005) find evidence that knowledge spillover is associated with trade. Markusen (2002) and Fosfuri, Motta and Ronde (2001) state that knowledge spills over through patents sharing among multi-national firms and is linked to foreign direct investment. To provide a basis for investigating knowledge diffusion within a numerical general equilibrium framework, we use basic regression analysis to derive sector- and region-specific parameters describing the accessibility and elasticity of innovative outcomes with respect to different types of knowledge spillovers (domestic intra-sectoral spillovers, domestic inter-sectoral spillovers domestic, and foreign intra-sectoral spillovers).

Our paper is also related to the literature on modeling technology innovation and the economic effects of climate policy. Besides the empirical work by (for example, Popp, 2002; Zwaan et al., 2002; Calel and Dechezleprêtre, 2016; Aghion et al., 2016), numerical modeling of impacts of climate policy predominantly adopts an exogenous growth framework and assumes that knowledge diffusion is entirely absent or limited (Bosetti et al. 2008; Carbone, Helm and Rutherford 2009). Early work by Bovenberg and Smulders (1995, 1996) and Goulder and Schneider (1999) examine endogenous innovations in carbon dioxide abatement technologies. Manne and Richels (2004), Fischer and Newell (2008), and Massetti, Carraro and Nicita (2009) investigate the response of technology to environmental regulation. None of these studies, however, consider knowledge diffusion. Bretschger, Ramer and Schwark (2011) assumes a small open economy with endogenous growth but abstracts from international and intersectoral knowledge spillovers. Somewhat similar to our paper,

[4]The flow of new information and ideas, contributing to a single worldwide research sector, has been shown to have positive effects on growth (Rivera-Batiz and Romer, 1991). In fact, Grossman and Helpman (2015) view international knowledge spillovers as a key mechanism tightly linking globalization and regional development through size and competition effects.

Diao, Roe and Yeldan (1999) and Bye, Faehn and Heggedal (2009, 2011) account explicitly for cross-border technological spillovers within a numerical endogenous growth model. These studies, however, assume a small open economy setting which does not enable the explicit analysis of international knowledge diffusion; moreover, empirical estimates for spillovers are based on previous, rather old studies (Coe and Helpman, 1995; Keller, 2004).

The remainder of this paper is organized as follows. Section I presents the model. Section II describes our empirical strategy to estimate knowledge diffusion and calibrate the numerical model. Section III presents and discusses our simulation results. Section IV concludes. Appendix A contains additional information on econometric results and model parameters. Appendix B compares the results of our baseline model without knowledge diffusion with those from existing comparable studies.

I. Model

This section presents our model, which is an infinite-horizon discrete-time dynamic general equilibrium setup of the global economy with multiple regions and sectors. Sectoral output in each region combines intermediates produced under monopolistic competition using physical and knowledge capital, labor, and different types of energy (coal, natural gas, crude oil, refined oil, electricity). Endogenous growth is driven by increasing gains from specialization within a sector. In addition, knowledge diffuses between sectors and regions depending on the accessibility and absorptive capacity of firms. Carbon emissions derive from burning fossil fuels in production and consumption. We next describe each aspect of the model in turn and characterize the equilibrium.

A. *Production Technologies for Sectoral and Intermediate Goods*

SECTORAL OUTPUT.—Production of final output in each sector is characterized by a three-stage process. At the first stage, final output Y_{irt} in sector $i \in I$, region r, at time t, is produced with a sector-specific intermediate composite Q_{irt} and a composite output from other sectors B_{irt}:

$$Y_{irt} = [\alpha_{ir} Q_{irt}^{\frac{\gamma_{ir}-1}{\gamma_{ir}}} + (1-\alpha_{ir}) B_{irt}^{\frac{\gamma_{ir}-1}{\gamma_{ir}}})]^{\frac{\gamma_{ir}}{\gamma_{ir}-1}} \tag{1}$$

where α_{ir} is a share parameter and $\gamma_{ir} > 0$ denotes the elasticity of input substitution. Final good producers at time t maximize static profits under perfect competition:

$$\max_{Q_{irt}, B_{irt}} p_{irt}^{Y} Y_{irt} - p_{irt}^{Q} Q_{irt} - p_{irt}^{B} B_{irt} \tag{2}$$

subject to (1) and taking prices of Y, Q, and B, denoted by p^Y, p^Q, and p^B, respectively, as given. This implies optimal relative input demand according to:

$$\frac{Q_{irt}}{B_{irt}} = \left(\frac{\alpha_{ir}}{1-\alpha_{ir}}\right)^{\gamma_{ir}} \left(\frac{p^Q_{irt}}{p^B_{irt}}\right)^{-\gamma_{ir}} , \tag{3}$$

so that *ceteris paribus* a decrease of the sector-specific output price p^Q induces higher input use Q and higher sectoral output Y, raising the output in the economy.

INTERMEDIATE COMPOSITE.—At the second stage of the production process we introduce endogenous growth by building on the well-known variety approach (Romer, 1990) where endogenous growth is driven by increasing gains from specialization. Following Dixit and Stiglitz (1977), intermediate composite Q_{irt} is produced by combining varieties produced by firm j in sector i, x_{jirt}, according to:

$$Q_{irt} = \left[\int_{j=0}^{J_{irt}} x^{\kappa}_{jirt}\, dj\right]^{\frac{1}{\kappa}} \tag{4}$$

where J_{irt} is the total number of intermediate varieties in sector i and region r available at time t and $\kappa \in (0,1)$ measures the gains from diversification.

The profit maximization problem for intermediate composite producers is:

$$\max_{x_{jirt}} p^Q_{irt} Q_{irt} - \int_{j=0}^{J_{irt}} p^x_{jirt} x_{jirt}\, dj \tag{5}$$

subject to the constraint (4), yielding the optimal demand for the good x_{jirt}:

$$x_{jirt} = \left(\frac{p^Q_{irt}}{p^x_{jirt}}\right)^{\frac{1}{1-\kappa}} Q_{irt} , \tag{6}$$

which implicitly defines the price of x_{jirt}, p^x_{jirt}. Given that intermediate goods are imperfect substitutes for each other and that there is monopolistic competition among intermediate goods producers, optimal pricing from (6) yields p^x_{jirt} equals the marginal cost of producing x_{jirt} plus a mark-up equal to $1/\kappa$.

Assuming symmetric intermediate goods, i.e. $x_{jirt} = x_{irt}$, intermediate composite output can be written as:

$$Q_{irt} = J^{1/\kappa}_{irt} x_{irt} . \tag{7}$$

Intuitively, output Q can be increased by either producing a larger quantity per firm (x) with a given number of varieties or by increasing the number of varieties (J) with given aggregate firms' inputs ($\sum_i x_{irt}$).

INTERMEDIATE GOODS.—At the bottom level of sectoral production, intermediate goods x_{irt} are produced by combining labor L and energy E according to a constant-

elasticity-of-substitution (CES) function:

$$x_{irt} = J_{irt}[\phi_{ir} L_{irt}^{\frac{\nu_{ir}-1}{\nu_{ir}}} + (1-\phi_{ir}) E_{irt}^{\frac{\nu_{ir}-1}{\nu_{ir}}}]^{\frac{\nu_{ir}}{\nu_{ir}-1}} \tag{8}$$

where ϕ_{ir} and $1-\phi_{ir}$ are share parameters and ν_{ir} is the elasticity of substitution. J_{irt} reflects the productivity in the production of intermediates at the sectoral level. The aggregate energy input E_{irt} is a CES composite of different types of energy (coal, natural gas, refined oil, electricity):

$$E_{irt} = [\sum_k \vartheta_{kir} (Z_{kirt})^{\frac{\omega_{ir}-1}{\omega_{ir}}}]^{\frac{\omega_{ir}}{\omega_{ir}-1}} \tag{9}$$

where Z_{kirt} is the amount of energy of type $k \in K \subset I$ used in sector i and region r at time t. ϑ_{kir} and ω_{kir} denote share and elasticity of substitution parameters, respectively. The profit maximization problem of intermediate goods producer i at time t solves:

$$\max_{L_{irt}, Z_{kirt}} p_{irt}^x x_{irt} - w_{rt} L_{irt} - \sum_k p_{krt}^A Z_{kirt} \tag{10}$$

subject to (8) and (9) taking prices as given.

B. *International Trade and Supply of Final Goods*

We assume that all sectoral goods are tradable. Sector-specific bilateral international trade is represented following the standard Armington (1969) approach where goods produced at different locations are treated as imperfect substitutes. The amount of final good i supplied in region r at time t, A_{irt}, is thus given by a composite of sectoral outputs produced domestically and abroad:

$$A_{irt} = [\varsigma_{ir} D_{irt}^{\frac{\eta_{ir}-1}{\eta_{ir}}} + (1-\varsigma_{ir}) \underbrace{\{(\sum_{s \neq r} m_{isr} M_{isrt}^{\frac{\psi_{ir}-1}{\psi_{ir}}})^{\frac{\psi_{ir}}{(\psi_{ir}-1)}}\}}_{= \text{CES import aggregate}}^{\frac{(\eta_{ir}-1)}{\eta_{ir}}}]^{\frac{\eta_{ir}}{\eta_{ir}-1}} \tag{11}$$

where D_{irt} denotes domestic supply and M_{isrt} represents imports of final good i from region s to region r which are aggregated in a CES fashion. ς_{ir}, m_{isr}, η_{ir}, and ψ_{ir} denote share and elasticity of substitution parameters, respectively.

The final goods supplier i in region r at time t maximizes profits taking prices as given according to:

$$\max_{D_{irt}, M_{isrt}} p_{irt}^A A_{irt} - p_{irt}^Y D_{irt} - \sum_{s \neq r} p_{ist}^A M_{isrt} \tag{12}$$

subject to (11).

C. Investment and Intertemporal Capital Accumulation

The number of varieties in each sector and region is determined endogenously. Investments in new varieties are based on a purposeful decision by rational agents. New growth theory uses the assumption that a new intermediate variety needs a "patent" or a "blueprint" to be produced (Romer, 1990). Firms are the owners of the blueprint or patent, which is knowledge capital constituting the firm value. Applying this theoretical approach to real-world economies, physical capital has to be added to knowledge capital as it constitutes an important determinant of the firm value. We assume that each new intermediate firm owns a new "composite" capital good which consists of physical and non-physical capital.[5]

Firms enter and exit freely into sector-specific investment activities. The profits from intermediate goods production are fully transferred to the households owning the intermediate firms. In equilibrium, firm ownership yields the same return as a riskless loan. Specifically, investments are expanded up to the point where marginal costs equal the firm value.

In an equilibrium with positive investment ($I_{irt} > 0$), the cost of a composite investment good equals the firm value. The no-arbitrage condition for investments states that an investment in a new firm with the price p^I_{irt}, yielding a direct return π_{irt}, entailing a capital gain or loss of $p^J_{irt+1}/(1+r_{irt}) - p^J_{irt}$ (measured in present value), and a loss due to capital depreciation of $\delta_t\, p^J_{irt}$ must have a return equal to an investment of the same size in a riskless loan with interest r_{irt}, so that:

$$\pi_{irt} + \frac{p^J_{irt+1}}{1+r_{irt}} - p^J_{irt} - \delta_t p^J_{irt} = r_{irt} \cdot p^I_{irt}\,,$$

where profits per firm (or per unit of capital) are given by: $\pi_{irt} = (1-\kappa)p^Q_{irt}Q_{irt}/J_{irt}$.[6] Inserting π into the above equation and dividing by p^I_{irt} yields the capital rental market equilibrium:

$$\frac{p^J_{irt}}{p^I_{irt}}[\underbrace{(1-\kappa)\frac{p^Q_{irt}}{p^J_{irt}}Q_{irt}/J_{irt}}_{\substack{\text{=rate of}\\ \text{per-firm profits}}} + \underbrace{\frac{p^J_{irt+1}}{(1+r_{irt})p^J_{irt}}}_{\substack{\text{=change in}\\ \text{capital value}}} - 1 - \delta_t] = r_{irt} \tag{13}$$

expressing that the capital return net of depreciation equals the interest rate r_t.

The sector- and region-specific capital stocks at time $t+1$, J_{irt+1} are determined

[5] Following the seminal contribution by Suzuki (1976), we assume that knowledge capital and physical capital are perfect substitutes. Our analysis thus rests on a broad-based concept of capital. With an eye on carrying out an empirical quantitative analysis, this assumption is mainly motivated by the lack of data that prevent us from adequately measuring knowledge capital in a multi-region global economy. While being beyond the scope of this paper, we leave for future research the analysis of how introducing different types of capital would affect our results.

[6] Note from (4) that $(1-\kappa)$ represents the share of sectoral revenue $p^Q_{irt}Q_{irt}$ which is used to compensate intermediate firms for their investment activities.

Table 1. Four types of knowledge spillovers

	Intra-sectoral	Inter-sectoral
Domestic	A	B
Inter-regional	C	D

by (1) investments into new varieties in time t, (2) the size of the (beginning-of-period) knowledge stock in time t, and (3) the capital increment in time t due to knowledge diffusion, ΔJ_{irt}:

$$J_{irt+1} = I_{irt} + (1 - \delta_t)(\Delta J_{irt} + J_{irt}). \tag{14}$$

D. Knowledge Diffusion

BASIC MECHANISM.—We now introduce the mechanics of knowledge diffusion in our model that determine ΔJ_{irt}. Due to the non-rivalry property of technologies, anyone engaged in capital accumulation has access to the economy's entire stock of knowledge which we will refer to as spillover from own knowledge. When allowing for free exchange of ideas between regions by assuming open communication networks it means that, when making investment decisions, each region has access to the other regions' knowledge stock which we will refer to as interregional spillover. Investments in one region in a given period are thus a function of the own knowledge stock and the knowledge stock of other regions. If the stocks of ideas in each country are not perfectly overlapping, as has been shown by Rivera-Batiz and Romer (1991), the effective stock of knowledge that could be used in research through integration would be larger than in the case of isolation. This, in turn, increases productivity of capital accumulation, which fosters the rate of investments and induces higher economic growth.

KNOWLEDGE DISSEMINATION.—To study growth effects in a multi-regional and multi-sectoral economy, we extend the conventional notion of knowledge diffusion to cover the following four channels for the exchange of ideas (Table 1): domestic intra-sectoral spillovers (A), domestic inter-sectoral spillovers domestic (B), foreign intra-sectoral spillovers, i.e. knowledge spillovers from foreign regions of the same sector (C), and foreign inter-sectoral spillovers, i.e. knowledge spillovers from foreign regions of other sectors (D).

When operationalizing our theoretical framework in the context of a numerical simulation model that is based on econometrically estimated knowledge diffusion processes, we are constrained by data availability issues. First, spillovers of type D cannot be estimated due to lack of data and are thus omitted from the subsequent analysis. Second, available data do not allows us to identify intertemporal knowledge spillovers.[7] Thus, while knowledge is accumulated over time according to (14),

[7]While the patent data we use to estimate knowledge spillovers is available for different years, we have to pool data over time to yield a sufficiently large sample size (see Section II).

we assume that spillovers of types A to C materialize contemporaneously, i.e. within a given period. Also note that by following the standard endogenous growth approach by Romer (1990), type-A spillovers are already embedded in the knowledge stock J due to sharing knowledge on the basis of gains from specialization at the sectoral level.

Following these ideas, and taking the own capital stock J to reflect the absorptive capacity of a region or sector, the knowledge increment from knowledge spillovers in region r and sector i is determined by:

$$\Delta J_{irt} = f\left(J_{irt}, J^B_{irt}, J^C_{irt}\right) . \tag{15}$$

EFFECTIVE KNOWLEDGE AND ACCESSIBILITY.—Sectoral and regional diversity in the spillover process is represented by assuming imperfect accessibility of external knowledge stocks. Following a concept from the empirical literature on knowledge flows and innovation (e.g., Griliches, 1992 and Peri, 2005), we distinguish between knowledge flows and their subsequent effects on innovative outcomes. The knowledge flow describes the process whereby an idea generated by a certain region and sector is learned by another region and sector.[8] The effect of these knowledge flows represents the impact of the idea which has been learned by a region and sector on its innovative output.

We capture the diversity in bilateral knowledge flows between sectors and regions by constructing accessible external knowledge stocks. For sector i in region r at time t, the inter-sectoral domestic accessible knowledge stock J^B_{irt} and the intra-sectoral foreign accessible knowledge stock J^C_{irt} are given by:

$$J^B_{irt} = \sum_{h \neq i} \phi^B_{hir} J_{hrt}, \tag{16}$$

$$J^C_{irt} = \sum_{s \neq r} \phi^C_{isr} J_{ist}, \tag{17}$$

where s and h are indexes for regions and sectors, respectively. If knowledge is completely and immediately diffusible to all sectors and regions, then $\phi^B_{hir} = 1$ and $\phi^C_{isr} = 1 \; \forall r, i, h, s$; otherwise, $\phi^B_{hir}, \phi^C_{isr} \in [0, 1)$. The ϕ terms can be viewed as "accessibility parameters" representing weights for bilateral accessibility, in turn reflecting geographical and technological barriers for knowledge diffusion between regions and sectors.

SUBSTITUTABILITY OF KNOWLEDGE.—The effects of accessible knowledge stocks on the innovative output can be formalized as elasticities which describe the respon-

[8] As has been shown by the empirical literature, these knowledge flows depend on bilateral characteristics of regions, such as distance and languages, as well as on the bilateral characteristics of the sectors, such as technological similarities (Jaffe, Trajtenberg and Henderson 1993, Maurseth 2002).

siveness of the innovative output to changes in the different pools of ideas.[9] Based on (15), the partial elasticity of innovative output in sector i in region r with regard to the different knowledge stocks is defined as:

$$\frac{J_{irt}}{\partial J_{irt}} \frac{\partial \Delta J_{irt}}{\Delta J_{irt}} = \varepsilon_{it}^{J} \tag{18}$$

$$\frac{J_{irt}^{B}}{\partial J_{irt}^{B}} \frac{\partial \Delta J_{irt}}{\Delta J_{irt}} = \varepsilon_{it}^{B} \tag{19}$$

$$\frac{J_{irt}^{C}}{\partial J_{irt}^{C}} \frac{\partial \Delta J_{irt}}{\Delta J_{irt}} = \varepsilon_{it}^{C} \,. \tag{20}$$

Equation (15) reflects the fundamental idea that both accessible knowledge and the self-knowledge stock matter when transforming the external knowledge inflow into usable knowledge. We operationalize (15) by assuming that the function $f(\cdot)$ follows a CES form. Usable knowledge in region r and sector i at time t is hence given by:

$$\Delta J_{irt} = [\varepsilon_i^J (J_{irt})^{\frac{\lambda-1}{\lambda}} + \varepsilon_i^B (J_{irt}^B)^{\frac{\lambda-1}{\lambda}} + \varepsilon_i^C (J_{irt}^C)^{\frac{\lambda-1}{\lambda}}]^{\frac{\lambda}{\lambda-1}} \,. \tag{21}$$

A number of remarks with respect to (21) are in order. First, barriers to the diffusion of the same type of knowledge (either type B or C) are captured through (16) and (17) which define accessible knowledge stocks J_{irt}^B and J_{irt}^C, respectively. Second, usable knowledge increases with different types of knowledge, including own knowledge. The partial effect of each accessible knowledge stock on usable knowledge, holding other knowledge stocks fixed, is measured by the partial elasticities ε_i^J, ε_i^B, and ε_i^C.[10] Third, transforming various knowledge flows into usable knowledge for production depends on the size of the own knowledge stock. This captures the notion of absorptive capacity as, for example, put forward in Cohen and Levinthal (1989).

Lastly, $\lambda \geq 0$ measures the degree of substitutability or complementarity between different types of knowledge. From the literature on knowledge diffusion there does not seem to emerge a clear view regarding λ. For example, Cohen and Levinthal (1989) and Spence (1984) assume that own R&D capital and spillovers are perfect substitutes. Other, mostly theoretical studies tend to assume a Cobb-Douglas

[9] We use elasticities as they represent relative changes in the variables and do not depend on the units of variables. This property will be useful later when we combine parameters derived from patent data—where knowledge is approximated by count data—with a continuous representation of knowledge in the numerical model.

[10] Note that ε_i^J does not reflect the effects from type-A knowledge spillovers; it rather measures the partial elasticity with respect to the own knowledge stock. For example, the marginal product of knowledge spillovers from knowledge type J_t given the CES form of (21) is: $\partial \Delta J_t / \partial J_t = \varepsilon^J (J_t / \Delta J_t)^{\lambda}$.

function which embeds an unitary elasticity of substitution to characterize the transformation process between different types of knowledge (Adam, 1990; Bretschger, 1999; Branstetter, 2001; Bosetti et al., 2008; Mancusi, 2008).[11]

In absence of a consensus view from the literature and, in particular, given the lack of empirical estimates for λ, it is a central theme of our analysis to examine the implications of alternative assumptions with regard to substitutability or complementarity between different types of knowledge. We consider a range of cases covering a situation in which different knowledge types are relatively poor substitutes ($\lambda = 1$) and an extreme case with perfect substitutability ($\lambda \to \infty$).[12]

In summary, knowledge at each point in time is propagated via intersectoral and international knowledge diffusions. Both accessible knowledge and self-knowledge stock matter when transforming the external inflow knowledge into usable knowledge. Barriers of knowledge flows are reflected by ϕ^B_{hir} and ϕ^C_{isr}, and the effect of accessible knowledge stocks on innovative output is reflected by elasticities ε^J_i, ε^B_{it}, ε^C_{it} and λ.

E. Preferences and Endowments

Each region r is inhabited by a representative household with lifetime utility given by

$$U_r = \sum_{t=0}^{\infty} \left(\frac{1}{1+\rho}\right)^t \frac{C_{rt}^{1-\theta} - 1}{1-\theta} \tag{22}$$

where $\rho > 0$ is the discount rate and θ the inverse of the elasticity of intertemporal substitution. C_{rt} is aggregate consumption by the representative household in region r at time t being a CES composite of sectoral final goods.

The representative household in region r is endowed with $\bar{L}_t$ units of labor which are supplied inelastically. It owns all the firms in the domestic economy and can lend and borrow freely with loans being perfect substitutes to capital. The household maximizes lifetime utility subject to the following period-by-period budget constraint, taking sector-specific interest rates r_{irt} and wages w_{rt} as given:

$$\sum_i^I p^J_{irt+1} J_{irt+1} = w_{rt}\bar{L}_{rt} - T_{rt} - p^C_{rt} C_{rt} + \sum_i^I (1 + r_{irt}) p^J_{irt} J_{irt} \tag{23}$$

where T_{rt} is the net lump-sum tax (or transfer) used for balancing the government budget. p^C_{rt} is the price index of aggregate consumption according to a CES aggre-

[11] In theoretical work, the assumption of an unitary elasticity of substitution is often convenient as it eases analytical tractability.

[12] Note also that our econometric approach to estimate the partial elasticity parameters ε and barriers to knowledge diffusion ϕ does not invoke any assumption or restriction on λ (see Section II). For the purpose of the numerical analysis, we thus treat λ as a free parameter.

gation of final goods as given by:

$$p^C_{rt} = [\sum_i c_{ir}(p^A_{irt})^{1-n}]^{1/1-n} \tag{24}$$

where c_{ir} and n are share and elasticity of substitution parameters, respectively.

F. Markets and Pricing

To characterize equilibrium prices, we define additional market clearing and pricing conditions. The market for sectoral output clears if:

$$Y_{irt} = D_{irt} + \sum_{s \neq r} M_{irst}\,. \tag{25}$$

In our multi-sectoral setup, the composite good for each sector i for investment and intermediate demand purposes is produced by combining Armington goods according to a CES aggregation under perfect competition. Solving the related profit maximization problem yields the respective price indexes (i.e., unit expenditure functions):

$$p^u_{irt} = [\sum_{i'} \theta^u_{i'ir}(p^A_{i'rt})^{1-\sigma^u}]^{1/1-\sigma^u} \tag{26}$$

where $\theta^u_{i'ir}$ is the cost share of good i' in the production of final demand category $u = \{I, B\}$ in sector i, and σ^u are respective substitution parameters.

Final goods can be used for production (B_{irt}), consumption (C_{rt}), and investment (I_{rt}). For each of these final demand categories, Armington goods are aggregated using a CES function. Let $\tilde{B}_{i'irt}$, $\tilde{C}_{irt}$, and investment $\tilde{I}_{i'irt}$ denote the cost-minimizing input demand for production, consumption, and investment purposes of final good A_{irt}, respectively. The price for final goods, $\tilde{p}^A_{irt}$, is then determined by the following market clearing condition:

$$A_{irt} = \tilde{C}_{irt} + \sum_{i'} \tilde{I}_{i'irt} + \sum_{i' \neq k} \tilde{B}_{i'irt} + \sum_{i' \text{ if } i \subset K} \tilde{Z}_{ii'rt}\,. \tag{27}$$

The user price of final fossil-energy good e (where e comprises coal, natural gas, refined oil) includes the costs of carbon according to the carbon content of good e (Φ_e) and the carbon price (Υ_t):

$$p^A_{ert} = \tilde{p}^A_{ert} + \Phi_e \Upsilon_t\,. \tag{28}$$

Costs of carbon thus increase the price of final energy goods, reducing energy intensity in consumption, investment, and intermediate goods production. Carbon pricing also affect foreign trade by changing the relative prices of domestic and foreign goods.

Given a global climate policy $\{\Gamma_t\}_{t=0}^{\infty}$ that implements a time path of maximum allowable quantities Γ_t of global CO_2 emissions in each period, the endogenous carbon price clears the market for emissions:[13]

$$\Gamma_t \geq \sum_r \frac{\partial p_{rt}^C}{\partial \Upsilon_t} C_{rt} + \sum_r \sum_i \left(\frac{\partial p_{irt}^I}{\partial \Upsilon_t} I_{irt} + \frac{\partial p_{irt}^x}{\partial \Upsilon_t} x_{irt} \right), \tag{29}$$

where on the right-hand side we exploit Shepard's Lemma to derive the optimal unit demands for carbon emissions.

Labor is treated as perfectly mobile between sectors within a region, but not mobile between regions. Accordingly, the domestic wage rate w_{rt} is determined on regional labor market:

$$\overline{L}_{rt} = \sum_i L_{irt} \,. \tag{30}$$

G. *Equilibrium*

We now summarize the dynamic equilibrium path using the equations we have derived in this section. For any given time path of climate policy $\{\Gamma_t\}_{t=0}^{\infty}$, a dynamic equilibrium path is characterized by a time path of quantities and prices

$$\{Y_{irt}, Q_{irt}, B_{irt}, x_{irt}, J_{irt}, L_{irt}, E_{irt}, Z_{kirt}, A_{irt}, D_{irt}, M_{isrt}, I_{irt}, \Delta J_{irt}, C_{rt}\}_{t=0}^{\infty}$$
$$\left\{p_{irt}^Y, p_{irt}^Q, p_{irt}^B, p_{irt}^x, p_{irt}^J, p_{irt}^I, r_{irt}, p_{irt}^A, w_{rt}, p_{rt}^C, \Upsilon_t\right\}_{t=0}^{\infty}$$

such that (1) Y_{irt}, Q_{irt}, and B_{irt} maximize profits as in (2) subject to (1); (2) intermediate goods production x_{irt} solves (5) subject to (4); (3) sector-specific capital stocks J_{irt}, investments I_{irt}, and aggregate consumption C_{rt} solves the households' intertemporal utility maximization problems as given by (22) subject to the resource constraint (23) and the law of motion (14); (4) labor and energy inputs L_{irt}, E_{irt}, and Z_{kirt} in intermediate goods production solve (10) subject to (8) and (9); (5) international trade pattern A_{irt}, D_{irt}, and M_{isrt} are determined by (12) subject to (11); (6) the dynamics for ΔJ_{irt} are determined by the knowledge diffusion module given by (16), (17), and (21); (7) prices for sectoral outputs p_{irt}^Y are determined by the market clearing condition (25); (8) p_{irt}^Q adjusts to balance supply (7) and demand (3); (9)p_{rt}^C is given by (24); (10) price for composite goods for investment and sectoral production p_{irt}^I and p_{irt}^B are given by (26); (10) intermediate goods prices p_{irt}^x equilibrate demand (6) and supply (7); (11) the price of capital p_{irt}^J clears the market for capital (14); (12) the interest rate r_{irt} is determined by the no-arbitrage condition (13); (13) the price for Armington goods p_{irt}^A clears the market for final goods (27); (14) the wage rate w_{rt} clear the labor market (30); and (15) the

[13] Given our model setup, the climate policy could be viewed as equivalently representing a uniform global carbon tax or a global emissions permit trading system.

endogenous carbon tax Υ_t is determined by the constraint on CO_2 emissions (29).

H. Model Mechanisms

ABSOLUTE AND RELATIVE SIZE EFFECTS.—In a one-sector closed economy, domestic investments fully determine the growth rate. In an economy with multiple sectors and regions, knowledge diffusion between sectors and regions has an additional effect on growth: knowledge inflow from external sources increases the capital-output ratio and the productivity of firms with positive effects on economic growth. We refer to this as the *size effect* of domestic and international knowledge diffusion.

The *absolute size effect* describes that more knowledge inflows increase the size of the capital stock (J), in turn enhancing both the number of varieties (equation (7)) and the productivity of intermediates firms (equation (8)). A higher substitutability between different knowledge types (higher λ) means that more usable knowledge can be created with a given amount of knowledge inflow (see equation (21)). In addition, for a given λ the *absolute size effect* increases in the size of own knowledge—reflecting the idea of absorptive capacity. The *relative size effect* describes that a given amount of knowledge inflow triggers a high impact for regions or sectors with a relatively small size of knowledge capital. This effect arises because different types of knowledge are imperfect substitutes, i.e. λ is less than infinity in the production of usable knowledge (see equation (21)).[14] As the production function of usable knowledge (21) exhibits diminishing marginal productivity with respect to each knowledge input, the magnitude of the *relative size effect* depends negatively on λ.

COMPETITION EFFECT.—Domestic and international knowledge diffusion has indirect effects through affecting the competitiveness of firms—which we refer to as the *competition effect*: a relatively large knowledge inflow boosts productivity enabling to sell products at lower prices in domestic and international markets. To see this, note that a higher J_{irt} lowers the unit-costs for the sector-specific intermediate composite Q_{irt}, in turn reducing the unit-costs for sectoral output Y_{irt}. Through international trade, this cost reduction feeds also through in the form of lower prices for exports M_{irt}. Note that while knowledge itself is a non-rival good, and hence the *size effects* can be viewed as being "non-rival", the *competition effect* is not neutral as traded goods are fully rival.

GREENING EFFECT AND IMPLICATIONS FOR COSTS OF CLIMATE POLICY.—The *size* and *competition effects* induced by knowledge diffusion bring about a "greening" of economies, i.e. clean carbon-extensive sectors grow faster than dirty carbon-intensive sectors. In our model, the forces behind the greening are as follows. First, the pollution per unit of output decreases as production becomes more productive. Second, the *absolute size effect* implies that green sectors attract relatively more knowledge because the are relatively capital-intensive. Knowledge diffusion thus increases the productivity of green sectors by more than it does for dirty sectors.

[14] If different knowledge types are perfect substitute ($\lambda \to \infty$), then a given amount of knowledge inflow translates into an equal increase in usable knowledge ΔJ.

Third, the *competition effect* implies that the sectoral composition of the economy shifts towards green production: as knowledge becomes more abundant through knowledge diffusion, the output of clean relative to dirty sectors increases because knowledge is used intensively in the production of green firms.[15] Opening up for knowledge transmission thus introduces specific growth support for green sectors and regions.

When energy (carbon) inputs become more costly under a climate policy regime, knowledge diffusion lowers the costs of substituting away from carbon-intensive goods because clean goods can be produced at lower costs. A higher productivity due to knowledge inflow lowers the cost share of carbon and following the carbon policy more resources are shifted to clean sectors which have become more productive relative to dirty sectors due to knowledge diffusion. In addition, the *relative size effect* means that these positive effects on the cost of climate policy are more pronounced for sectors and regions with relatively low initial knowledge. These positive effects are re-enforced (1) over time as the higher productivity of green sectors leads to higher growth for these sectors and (2) across space and markets due to increased competitiveness in domestic and international trade.[16]

II. Data and Empirical Strategy

To develop a *quantitative* version of our theory, a large number of region- and sector-specific parameters has to be determined. We proceed in four steps. First, we estimate knowledge diffusion parameters $\{\phi^B_{hir}, \phi^C_{isr}, \varepsilon^J_i, \varepsilon^B_{it}, \varepsilon^C_{it}, \lambda\}$ based on patent and citation data. Second, we characterize the sectoral production structure, investment, consumption, and bi-lateral international trade patterns of each regional economy consistent with observed Social Accounting Matrix data describing a benchmark equilibrium at a given base year. This enables us to infer value flows at time t=0 for quantity variables $\{Y^0_{ir}, Q^0_{ir}, B^0_{ir}, x^0_{ir}, J^0_{ir}, L^0_{ir}, E^0_{ir}, Z^0_{kir}, A^0_{ir}, D^0_{ir}, M^0_{isr}, I^0_{ir}, C^0_r\}$ and the share parameters $\{\alpha_{ir}, \phi_{ir}, \vartheta_{kir}, \varsigma_{ir}, m_{isr}, c_{ir}, \theta^u_{i'ir}\}$. Third, elasticity of substitution parameters in production and consumption $\{\gamma_{ir}, \nu_{ir}, \omega_{ir}, \eta_{ir}, \psi_{ir}, n, \sigma_u\}$ and the mark-up parameter κ are determined. Fourth, we construct a balanced growth path extrapolating regional economies from t=0 based on intertemporal household preferences $\{\rho, \theta\}$ and assumptions about rates of interest, output growth, and capital depreciation $\{\bar{r}, \bar{\gamma}, \delta_t\}$. We now describe each step of the model calibration in turn and finally describe our computational strategy.

[15] The *competition effect* could hence also be viewed as a "Rybczynski-type" effect known from the trade literature.

[16] One concern with endogenous growth models is the presence of "scale effects" which imply that countries with larger populations tend to grow faster (Jones, 1999; Segerstrom, 1998). Importantly, it implies that knowledge innovations get less expensive over time. This structural feature of our model is behind the result of the paper that knowledge diffusion reduces the cost of climate policy. While some data shows that inventions become more expensive to develop over time, there is also ample evidence that the costs of advanced and carbon-free energy technologies, such as solar and wind power, have been falling steadily (IEA, 2015; IPCC, 2014). To the extent that the costs of inventions increases over time, our model may overestimate the reductions in the costs of climate policy brought about by knowledge diffusion.

Table 2. Mapping of countries to regions

Region label	Countries
EUR	Austria, Belgium, Switzerland, Czech Republic, Denmark, Germany, Estonia, Spain, Finland, France, Great Britain, Greece, Ireland, Iceland, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Sweden, Slovenia, Slovakia
USA	USA
CHN	China
ROW	Rest of the World[a]

[a]Note that ROW includes here both developed and less developed countries. More specifically, it includes an aggregate of the remainder of the 129 regions in our dataset (see Section) from the GTAP (2008*a*) data after accounting for the European countries, USA, and China.

A. Estimation of Knowledge Diffusion Parameters

PATENT AND CITATION DATA.—We use patent data to empirically derive the knowledge spillover parameters. The idea of measuring innovation processes by patent data has a long tradition in the economic literature (Griliches, 1991).[17] For the purpose of investigating knowledge diffusion in a multi-sector and multi-regional context, we see the main advantage of patent data in the high degree of disaggregation at which they are available (at the technological and regional level, as well as across time).

We use patent applications at the European Patent Office (EPO) and corresponding citation data from the EPO World Patent Statistical Database (PATSTAT) and the OECD Citations Database. The selection of European patents is an appropriate choice to approximate international knowledge diffusion as it implies a focus on international patents representing high quality innovations (Mancusi, 2008).[18] In order to rigorously account for patents with international potential, we further restrict our focus to EPO patents which are part of the "Triadic Patent Family". These are patents which have been filed in US, European, and Japanese patent offices.[19] Our data set contains information on patents applied for at the EPO in the period from 1978 to 2013 by applicants located in a set of 37 countries. We aggregate applicants into four country groups (see Table 2) that correspond with the regional structure of the numerical model.

Each patent is assigned its priority data, which describes the date of first application in any country worldwide. This date is relevant from an economic and technological point of view as it is the closest to the date of invention. Following

[17]The advantages and limitations of using patent data have been broadly discussed in the literature (Jaffe 1999; Keller 2004; Mancusi 2008). A critical appraisal includes recognizing that not all innovations are patented as firms may prefer to hide their ideas for strategic reasons. Moreover, the "propensity to patent" differs across countries, industries, and firms. Also, not every patent has the same value in terms of commercial applications with some patented technologies never being used at large scale.

[18]Typically applicants at the EPO follow a two-stage procedure. First, they apply to their national patent office and afterwards to the EPO, which acts as a single intermediary to all participating country. Thus, the additional costs of the second application serve as a selection mechanisms for "good" innovation.

[19]Triadic patents have been used extensively as a way to identify high-value patents (Grupp, Muent and Schmoch (1996); Dernis and Guellec (2001); Dernis and Khan (2004)).

Table 3. Mapping of IPC sections to sectors

Sector label	Description	IPC sections (subsections)
AGR	Agriculture	A01 (Agriculture, Animal Husbandry, Hunting, Trapping, Fishing)
TRN	Transportation	B (Performing Operations, Transportation)
EIS	Energy-intensive manufacturing	C (Chemistry), D (Metallurgy), E (Textiles, Paper, Fixed Construction)
MAN	Other manufacturing	F (Mechanical engineering, Lighting, Heating, Weapons, Blasting)
ELE	Electricity	H (Electricity)

Dernis and Guellec (2001), we assign each patent to the country of residence of the first-named inventor in the patent document as it represents a good indicator for the innovative performance within a given country.

Following the sectoral structure of the numerical model, we assign patent data to different sectors by using the technology-based "International Patent Classification (IPC)". As the numerical model reflects an aggregated macroeconomic growth-framework, our approach is based on a highly generalized sectoral specification which implies a simple mapping from IPC sections and subsections into the economic sectors shown in Table 3.

KNOWLEDGE FLOWS AND ACCESSIBILITY.—We use citation counts to calculate the accessibility parameters. It is well-documented in the empirical literature that backward citation can be interpreted as a paper trail of knowledge flows between different regions or technologies as they reveal the relatedness between specific innovations (Keller, 2004). More specifically, a patent document contains references (citations) to prior inventions as the inventors are required to declare previous patents, which have been used to develop the new technology. This informs us that the researcher knows about an existing idea and that the idea has some relevance in the corresponding research process. Following prior empirical contributions (Peri, 2005), we measure the weights ϕ by calculating relative frequencies of patent citation between regions and sectors.

To further illustrate this idea, consider the weight for inter-sectoral domestic knowledge accessibility (type B spillover): for a given region r the accessibility of the knowledge stock in sector i from sector h is assigned the weight ϕ^B_{hir}. Using citation counts c, we calculate the corresponding accessibility weight between the two sectors as:

$$\hat{\phi}^B_{hir} = \frac{c_{hir}}{\sum_{n \neq h} c_{nir}}$$

where c_{hir} represents the citation number from patents classified into sector i to patents classified into technological field h within region r. Thus, the higher the share of citations from sector i to sector h relative to all other sectors n, the higher is the corresponding weight and, thus, the higher implied accessibility. For calculating the weights ϕ^C_{irs} cross-sectoral citations are included to ensure a large enough

TABLE 4. Summary statistics and pairwise correlations

	Mean	Std.Dev	dJ	J	J^B	J^C
dJ	1462.2	2410.0	1.00			
J	8861.9	16847.8	0.96	1.00		
J^B	3230.8	6892.3	0.43	0.45	1.00	
J^C	20643.2	19835.4	0.15	0.22	-0.06	1.00

number of inter-regional citations. Furthermore, we correct the inter-regional citation for country fixed effects thereby controlling for country-specific characteristics which are constant over time.

EFFECTS OF ACCESSIBLE KNOWLEDGE STOCKS ON INNOVATIVE OUTCOME.—Based on (15), we derive in a next step the effects of accessible knowledge stocks on the innovative output of sectors and regions (ε parameters). These estimates will be used to inform the numerical model on the magnitudes of the diffusion process and do not necessarily represent the structural parameters.

Using the weights for accessibility $\hat{\phi}^B_{hir}$ and $\hat{\phi}^C_{irs}$, we derive the external knowledge stocks based on (16) and (17). We use cumulative patent counts to construct region- and sector-specific knowledge stocks J_{ir}. The knowledge stock at the beginning of period t, J_{irt}, is calculated from the application of patents in the previous period ($dJ_{(ir,t-1)}$) with the perpetual inventory method:

$$J_{irt} = (1-\delta)J_{ir,(t-1)} + dJ_{ir,(t-1)}$$

where for $t = 1$ we use:

$$J_{ir1} = \frac{dJ_{ir,(t-1)}}{\delta + g_{ir}}\,.$$

We assume a depreciation rate δ of 15% (Hall and Mairesse,1995). g_{ir} is the region- and sector-specific growth rate of knowledge which we calculate as the average growth rate over the time period of our sample.

The elasticities of the innovative output with regard to the different knowledge stocks (ε^J, ε^B, and ε^C), as described in (18)–(20), are derived from regression analysis. We measure the increment of new knowledge (dJ_{irt}) by means of patent counts. Since the number of patents are non-negative integers, we assume that patent counts follow a Poisson distribution which results in the following Poisson estimation equation:

$$E\left(dJ_{irt}|J_{irt}, J^B_{irt}, J^C_{irt}, \omega_i, \mu_t\right) = \exp\left(\beta_J J_{irt} + \beta_B J^B_{irt} + \beta_C J^C_{irt} + \omega_i + \mu_t\right) \tag{31}$$

where r, i and t index region, sector, and time, respectively. ω_i and μ_t capture unobserved sector- and time-specific heterogeneity.

ESTIMATION RESULTS.—Table 4 provides summary statistics and pairwise correlations for variables in our sample. The number of observations N is 1190 with 7

Table 5. Estimation results

	Estimates Poisson regression			Implied elasticities by sector				
	Estimate	Standard error		AGR	TRN	EIS	ELE	MAN
β_J	0.036***	0.006	ε_i^J	0.112	0.408	0.496	0.399	0.195
β_B	0.069***	0.016	ε_i^B	0.541	0.224	0.093	0.083	0.186
β_C	0.011*	0.002	ε_i^C	0.066	0.337	0.341	0.242	0.157
Constant	4.600***	0.615						
AIC	1040517							

Notes: The model includes a full set of sector and year dummies. We use cluster-robust standard errors.All explanatory variables are expressed in per thousand units. $^{***}p < 0.01$. $^{*}p < 0.15$. AIC stands for the Akaike information criterion.

regions[20], 5 sectors, and 34 time periods (from 1977-2010).

Table 5 shows estimation results for β's which represent the contemporaneous sensitivity of the innovative output with regard to the different knowledge stocks. It is evident that innovative output is positively associated with the own and the external knowledge stocks. The effects are highly significant for the own and domestic knowledge stock. The parameter for the inter-regional elasticity is only significant at the 15% level. The parameters of the Poisson regression can be interpreted as semi-elasticities: an unit increase in the knowledge stocks corresponds to a relative change in output of approximately $100 \times \beta\%$. We use this property to calculate the partial elasticities ε_i^J, ε_i^B and ε_i^C—governing the transformation of external accessible knowledge into usable knowledge—in terms of average effects.

Consider the example of sectoral averages. Note that $1/\overline{J_i}$ is the average relative value of an unit increase of the own knowledge stock for sector i. Exploiting the property of semi-elasticities, the implicit (sector-specific) average elasticity of innovative outcome with regard to the own knowledge stock can then be expressed as:[21]

$$\beta_J \overline{J_i} = \varepsilon_i^J.$$

The presented concept of elasticities in the knowledge production function helps to bridge the gap between the different functional forms of the spillover process in the numerical growth model (Cobb-Douglas or CES functions) and the empirical specification (Poisson regression).

Table 5 displays the estimated implied elasticities for each sector. Apart from the agricultural sector, the sensitivity of innovative output appears to be highest with regard to the own knowledge stock. For the agricultural and manufacturing

[20]In order to have a large enough number of observations, the regions used in the estimation are grouped into seven regions instead of four. The final values used in our numerical model are sector-specific elasticities which are averaged over all regions, so that the estimated parameters can be used directly in the numerical model. The 7 regions are Europe, US, Russia, China, India, Other annexe 1 countries (Australia, Canada, Japan, New Zealand), and Other middle income countries (Brazil, South Korea, Turkey and South Africa)

[21]Similarly, we can calculate the implicit average elasticity of innovation outcomes with regard to type B and C knowledge stocks, respectively, as: $\beta_B \overline{J_i^B} = \varepsilon_i^B$ and $\beta_C \overline{J_i^C} = \varepsilon_i^C$. Note that our econometric approach only allows us to estimate average effects for the partial elasticities.

sector, innovative output is more sensitive to international and intrasectoral than to intranational and intersectoral knowledge stocks, whereas the converse applies to the remaining sectors. Table A1 in an appendix shows additional estimation results for $\hat{\phi}^B_{hir}$, and $\hat{\phi}^C_{irs}$.[22]

B. Calibration

MATCHING REGIONAL SOCIAL ACCOUNTING MATRIX DATA.— The parametrization of the multi-sectoral economic structure for each region as well as the trade linkages between regions are based on regional social accounting matrix (SAM) data. This study makes use of SAM data from the Global Trade Analysis Project (GTAP, 2008*b*) which provides a consistent set of global accounts of production, consumption, and bilateral trade as well as physical energy flows differentiated by primary and secondary energy carrier. Besides the sectors shown in Table 3, the model distinguishes four energy sectors (coal, natural gas, crude oil, refined oil) and the services sector which are direct aggregations of the 57 commodities in the GTAP data. Primary factors in the dataset include capital and labor. The model represents four major world regions as shown in Table 2 which are aggregates of the 113 countries and regions differentiated in the GTAP data.[23] We follow the standard calibration procedure in multi-sectoral numerical general equilibrium modeling (see, for example, Rutherford, 1995; Harrison, Rutherford and Tarr, 1997; Böhringer, Carbone and Rutherford, 2016) according to which production and consumption technologies are calibrated to replicate a single-period reference equilibrium consistent with the SAM data in the base year.[24]

EXTERNAL CALIBRATION.— The elasticity of substitution (EOS) parameters and the mark-up parameter $\{\gamma_{ir}, \nu_{ir}, \omega_{ir}, \eta_{ir}, \psi_{ir}, n, \sigma_u, \kappa\}$ are set exogenously. The choice of values for EOS parameters follows closely the MIT EPPA model (Paltsev et al., 2005; Chen et al., 2015), a numerical general equilibrium model which has been widely used for climate policy analysis. In particular, we set γ_{ir}=.5, ν_{ir}=1, and ω_{ir}=0.5 $\forall r, i$, n=0.25, and σ_u varies between 0.3-0.5 depending on the final use u. We use the econometrically estimated EOS parameters for Armington trade provided by Narayanan, Badri and McDougall (2012) (η_{ir} and ψ_{ir} vary between 1.9-6 depending on region and commodity). Following Bretschger, Ramer and Schwark

[22]Note that the estimated elasticity parameters ε^J_i, ε^B_i, and ε^C_i are assumed to be identical across regions. Unfortunately, the structure of our sample does not allow for a reasonable number of observations per region in order to derive robust estimates for region-specific elasticities.

[23]The exact aggregation schemes for sectors and regions and the aggregated benchmark data is available on request from the authors.

[24]For example, the CES production technology for output of sector i in region r in (1) can be globally characterized, given γ_{ir} and observed benchmark *values* for output and inputs Y^0_{ir}, Q^0_{ir}, B^0_{ir} from the SAM data, by calibrating the function coefficients for the corresponding unit cost function,

$$c_{ir}(p^Q_{irt}, p^B_{irt}) = Y^0_{ir}[\hat{\alpha}_{ir}(p^Q_{irt})^{1-\gamma_{ir}} + (1-\hat{\alpha}_{ir})(p^B_{irt})^{1-\gamma_{ir}}]^{1/(1-\gamma_{ir})}\,,$$

such that the value shares of Q in the production of Y, normalizing base-year prices to unity, are given by $\hat{\alpha}_{ir} = Q^0_{ir}/Y^0_{ir}$. A more detailed explanation can be found in, for example, Rutherford (2002).

(2011), we set κ=0.14.[25]

CALIBRATION OF BALANCED GROWTH PATH.—We calibrate the model with endogenous growth (type-A spillovers) but without type-B and type-C knowledge spillovers to a steady-state baseline extrapolated from the set of 2007 social accounting matrices using exogenous assumptions on the growth rate of output, the interest rate, the intertemporal elasticity of substitution, and capital depreciation rate in time 0 $\{\bar{\gamma}, \bar{r}, \theta, \delta_0\}$. The choice of the annual interest rate is important for the results of a long-term analysis like the present one. We use a value of $\bar{r} = 0.05$ for the net of tax return.[26] The initial annual capital depreciation rate is set to 0.07. $\bar{\gamma}$ is set to 0.02 reflecting roughly an annual average of the European or U.S. economic growth experience between 2004 and 2012. The capital depreciation rate (δ_t, $t > 0$) and the household time preference rate (ρ) are calibrated to ensure that the model is on a balanced growth path. Given a constant interest rate $\overline{r}$, the time-specific depreciation rate δ_t is endogenously determined by equation (13). Deriving the usual Keynes-Ramsey rule gives the growth rate of the economy along a balanced growth, i.e. $g = [(1+\overline{r}))/(1+\rho)]^{(1/\theta)}$, from which we can infer ρ. Lastly, given $\{\bar{r}, \bar{\gamma}, \delta_0\}$ we use data on base-year capital earnings from the regional social accounting matrices (GTAP, 2008*b*) to infer regional capital stocks at $t = 0$.

C. *Computational Strategy*

Following Mathiesen (1985) and Rutherford (1995), we formulate the model as a mixed complementarity problem associating quantities with zero-profit and prices with market-clearing conditions. To approximate the infinite horizon global economy by a finite-dimensional computational problem, we use state-variable targeting (Lau, Pahlke and Rutherford, 2002). Importantly, this allows us to target the terminal capital stocks by sector, and thus an endogenous growth rate of the overall economy on a new balanced growth path, by using a series of complementarity constraints on the growth rates of sectoral investments. We use the General Algebraic Modeling System (GAMS) software and the GAMS/MPSGE higher-level language (Rutherford, 1999) together with the PATH solver (Dirkse and Ferris, 1995) to compute the equilibrium. We solve the model for 100 years.[27]

[25] Given that κ determines in our setup the strength of the endogenous growth mechanism and is highly uncertain, we perform sensitivity analysis with respect to κ, showing that our qualitative insights do not depend on the choice of κ (see Section III.C).

[26] Altig et al. (2001) argue for using a value around 7-8% based on the historical real rate of return to capital, while others (e.g., Fullerton and Rogers, 1993) use a much smaller rate around 3-4%. With no account for risk in this model it is not clear which value should be used. Also it should be kept in mind that with these kind of models there is no "correct" value.

[27] Solving the model for longer time horizons does not produce different results, thus indicating that the model has been given enough time to settle on a new balanced growth path.

III. Simulation Results

A. Impacts of Knowledge Diffusion on Welfare and Economic Growth

To quantitatively investigate the impact of domestic and international knowledge diffusion on economic welfare and growth, we use counter-factual analysis comparing worlds with and without knowledge spillovers.[28] We focus on obtaining insights into the relative importance of domestic and international spillovers, regional differences in knowledge accumulation over time, and ensuing economic impacts through changing productivity in the production of goods and services and through changing comparative advantages in international trade.

GLOBAL IMPACTS.—Figure 1 reports global and regional welfare impacts (measured as percentage change of lifetime utility) from comparing a world with and without domestic and international spillovers for alternative values for λ. The following insights emerge. First, and not surprisingly, knowledge diffusion increases welfare in all regions as higher levels of knowledge capital increase at zero costs the productivity with which non-knowledge inputs (labor and materials) can be combined to produce industry outputs. Welfare gains for the global economy are substantial ranging from about 4 to 10% depending on λ.

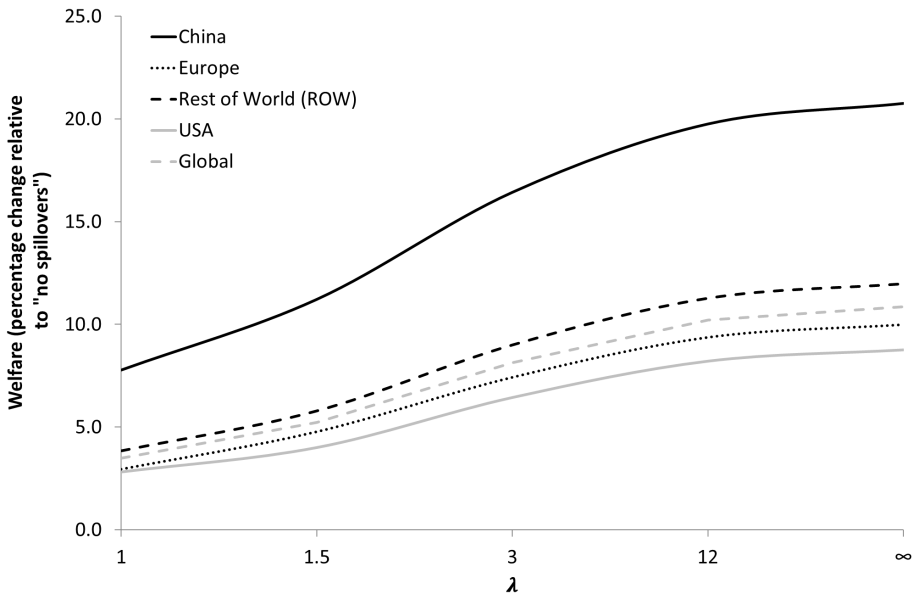
Second, welfare gains strongly increase with λ. A higher λ reflects the idea that different knowledge types can be combined more effectively. The case of perfect substitutes indicates that sizeable welfare gains from knowledge diffusion are possible; however, as there seem to be significant overlaps when combining knowledge, the notion of perfect substitutability between different types of knowledge should probably be best viewed as a limiting case which provides an upper bound for welfare gains.

Third, the marginal product of knowledge diffusion is always positive, and is first increasing and then decreasing in λ (S-shaped pattern of impacts in Figure 1). Increasing λ enables to better substitute with other types of knowledge, hence preventing diminishing returns to knowledge diffusion *from all types of knowledge*. Hence, marginal returns to *total* knowledge diffusion first increase as declining marginal returns of diffusion from one type of knowledge can be avoided. For high λ's, substitution possibilities between different knowledge types have been exhausted and the overall marginal product declines and eventually falls to zero (see almost flat parts of welfare impact curves as $\lambda \to \infty$). This reflects our assumption that while more knowledge becomes accessible through knowledge diffusion, the increments of *effective* new knowledge become smaller.

REGIONAL IMPACTS.—Why do regions benefit differently from knowledge spillovers? What are the patterns of regional knowledge diffusion in the global economy?

[28] In the (hypothetical) world without spillovers, we assume that the global economy is on a balanced growth path and contemporaneous type-B and type-C spillovers are suppressed (i.e., all ϕ's are zero). In all scenarios we assume that Romer-type spillovers between firms in the same industry (type A) are present thus giving rise to endogenous long-run growth. Our assessment of knowledge diffusion thus only pertains to domestic and international spillovers that are added to an otherwise standard Romer-type endogenous growth framework.

FIGURE 1. Global and regional welfare impacts of knowledge spillovers for different λ



How important are different types of knowledge spillovers for enhancing productivity and regional welfare?

A major determinant of regional welfare impacts is the amount of knowledge each region receives due to spillovers. The first line in Table 6 reports the relative size of knowledge increases due to domestic and international spillovers for each region. ROW obtains the largest increase, followed by Europe and the USA. China's increase in knowledge due to spillovers is about four times smaller compared to the ROW, about three times smaller than in Europe and roughly the half of the increase in the USA (depending on λ). These differences are mainly driven by the size of domestic spillovers. As China has by far the smallest initial capital stock (i.e., existing knowledge stock, see the second line in Table 6) the size of domestic inter-industry spillovers in China is much smaller as in other regions, regardless of differences in inter-industry spillover intensities. Focusing on the size of regional knowledge spillovers is, however, not a good indicator for regional welfare impacts. As Figure 1 shows, the welfare impacts from knowledge diffusion in China are about twice as large as compared to Europe and about 2.5 times bigger than those in the USA.

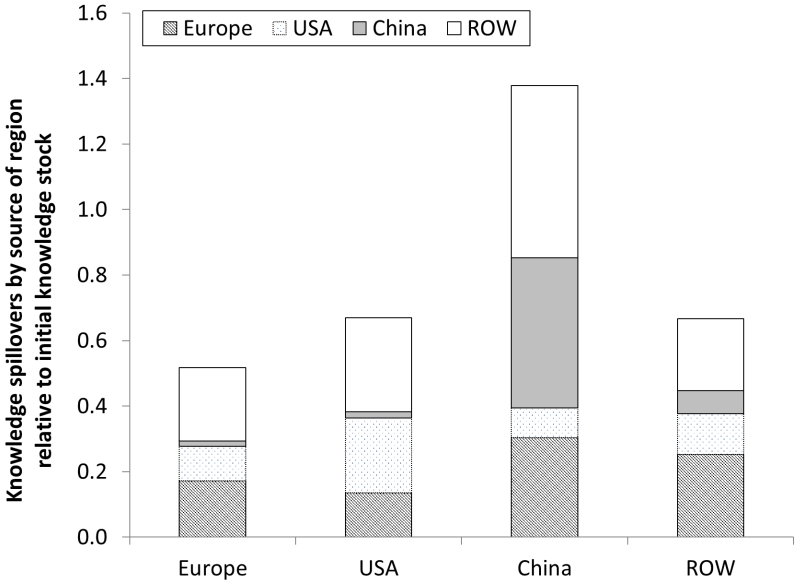
What matters is the size of regional knowledge spillovers *relative* to the existing stock of knowledge capital. Figure 2 shows the additions to regional knowledge capital due to domestic inter-industry spillovers and international same-industry spillovers where the latter is broken down source (i.e., region). Knowledge spillovers shown here comprise spillovers to all sectors and refer to cumulative spillovers in the period from 2010-2060. Moreover, we normalize knowledge flows relative to the

Table 6. Simulation results for key variables

	Europe			USA			China			ROW		
	$\lambda = 1$	$\lambda = 3$	$\lambda \to \infty$	$\lambda = 1$	$\lambda = 3$	$\lambda \to \infty$	$\lambda = 1$	$\lambda = 3$	$\lambda \to \infty$	$\lambda = 1$	$\lambda = 3$	$\lambda \to \infty$
Knowledge capital accumulation												
Relative size of initial capital stock[a]	0.34	–	–	0.18	–	–	0.08	–	–	0.40	–	–
Regional capital stock over time[b]												
Year 2030	2.7	6.1	7.9	3.9	8.1	10.4	7.1	13.7	16.6	3.6	8.1	10.2
Year 2060	3.1	7.3	9.4	4.2	9.3	11.9	7.3	15.2	18.5	4.0	9.4	11.8
Relative size of knowledge increase due to spillovers[a]	0.67	0.66	0.69	0.45	0.42	0.44	0.40	0.31	0.30	1.00	1.00	1.00
Private consumption												
Private consumption over time[c]												
Year 2010	2.2	5.5	5.1	2.0	4.4	4.1	6.8	13.9	10.2	3.0	6.9	6.1
Year 2060	3.3	8.5	11.3	3.2	7.5	10.1	8.2	17.7	22.3	4.2	10.1	13.4
Average annual growth rate (%)	2.36	2.41	2.37	2.37	2.41	2.37	2.37	2.42	2.37	2.37	2.41	2.37
Welfare decomposition by spillover type[c]												
Full spillovers	3.0	7.4	10.0	2.8	6.4	8.8	7.8	16.4	20.7	3.9	9.0	12.0
Only domestic spillovers ($\phi^c = 0$)	0.2	1.9	3.7	0.2	1.5	2.7	0.4	2.2	3.8	0.1	2.2	4.2
Only international ($\phi^b = 0$)	2.1	5.0	7.2	1.8	4.6	6.9	6.7	13.6	18.1	2.1	6.2	9.0

Notes: [a]Share in base-year global capital stock. [b]Based on cumulative (year 2010-2060) knowledge spillovers and normalized to 1 for ROW. [c]Percentage change relative to "no spillovers".

FIGURE 2. Source-destination patterns of domestic and international knowledge spillovers (all sectors aggregated and for $\lambda = 1$)



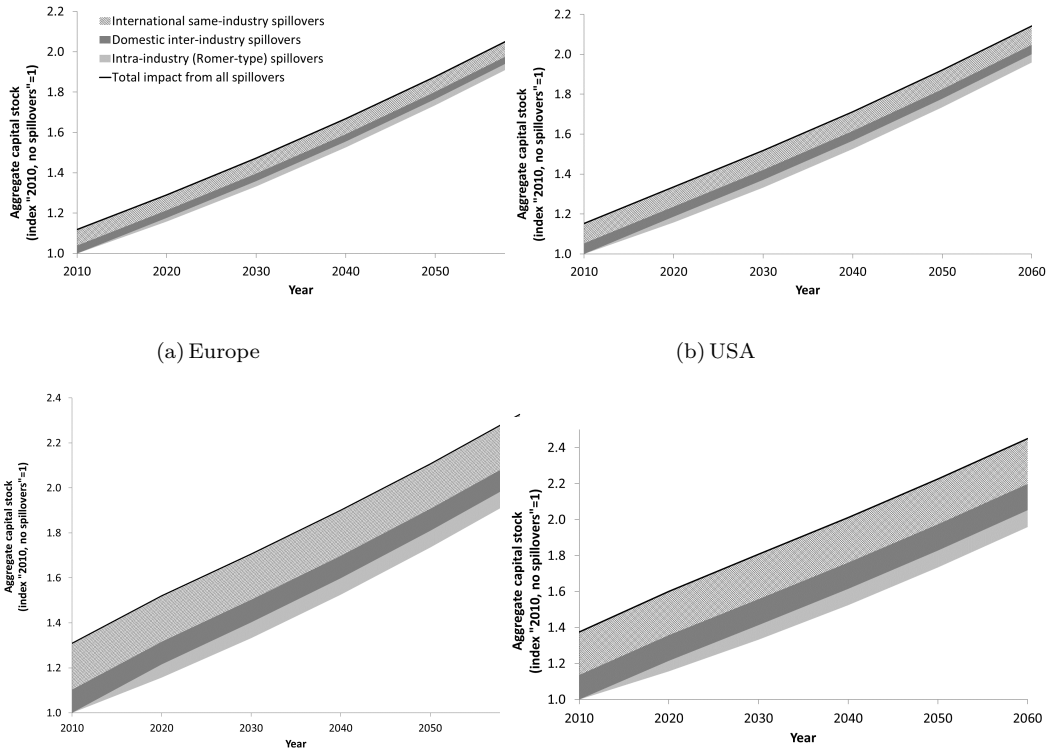
initial existing knowledge stock in each respective region.

Three main insights are borne out by Figure 2. First, for all regions the increase in knowledge capital is substantial, i.e. cumulative knowledge spillovers between 2010-2060 amount to roughly the size of the (annual) existing knowledge capital stock. Second, the increase in knowledge due to spillovers in China relative to its own, existing capital stock is about 1.4—which is significantly larger as compared to the other regions. As China has a relatively low share of capital in the global economy (see the second line in Table 6), the marginal productivity of the added knowledge is larger in China than in the other world regions. This explains why welfare gains due to knowledge diffusion are the largest in China. Third, it is evident that international knowledge diffusion constitutes a quantitatively important channel relative to domestic spillovers: only about one third of the knowledge increase relative to existing knowledge capital comes from domestic inter-industry spillovers (this is roughly similar for all regions and increases up to about 40% as $\lambda \to \infty$); about two thirds of the knowledge increase stem from international spillovers.

Why are the welfare gains the smallest for the USA—although Figure 2 shows that the knowledge increase in the USA is of comparable magnitude? The difference between Europe and the USA can be traced back to the international spillover intensity (ϕ^c's) between both regions.[29] The USA has much smaller coefficients

[29]The international industry-specific spillover coefficients for Europe and the USA vis-à-vis the ROW, which has the largest capital stock, are relatively similar. The USA shows slightly higher spillover coefficients than Europe vis-à-vis China; however, the capital stock in China is relatively small, hence this does not

FIGURE 3. Contemporaneous knowledge spillovers by type and intertemporal knowledge accumulation with and without spillovers



(a) Europe (b) USA

(c) China (d) ROW

Notes: Lower contour indicates capital stock in "no spillovers" case. Upper contour (=black line) indicates capital stock in world with spillovers. Cases shown assume $\lambda = 1$.

vis-à-vis Europe than Europe has vis-à-vis the USA. Although the existing capital stock in Europe is almost twice as large as the one in the USA (see the second line in Table 6), the knowledge flows from Europe to the USA are much smaller than from the USA to Europe. This explains why the USA benefits in our model less from international knowledge diffusion than Europe. The ROW exhibits the second largest welfare gains as the knowledge increase relative to its existing capital stock are relatively high (see Figure 2).

Figure 3 sheds some light on the interplay of contemporaneous knowledge spillovers and the intertemporal knowledge capital accumulation: it also quantifies the relative contributions of different types of knowledge. For each region, we compare the evolution of the knowledge capital stock over time in a world without (lower contour of the plots) and with (upper contour or black line) spillovers. We again normalize regional capital stocks relative to the existing knowledge capital stock in in each

have a large effect on the difference in welfare gains between the two countries.

region. In our endogenous growth framework, knowledge diffusion leads to productivity increases within industries. While the size of these *additional* "Romer-type" intra-industry spillovers is smaller than knowledge increases emanating from international and domestic inter-industry spillovers, they increase the growth rate of capital stocks. This can be seen in Figure 3 by noting that without the intra-industry spillovers (light-grey shaded area), the addition of knowledge due to domestic inter-industry and international spillovers would result in a (roughly) parallel shift of the lower contour; with "Romer-type" spillovers, the slope increases. The increase in the growth rate is the largest for China, consistent with the relatively large welfare gains in China. While Figure 3 shows only the case for $\lambda = 1$, Table 6 shows that the increases in the knowledge capital stock for all regions increase with λ. Figure 3 also underscores our finding that international spillovers bring about larger knowledge increases as compared to domestic (intra- and inter-industry) spillovers.

A potentially important channel through which knowledge diffusion can impact regional welfare and growth is international trade. As knowledge spillovers enhance productivity, the cost of producing goods and service are reduced, in turn affecting the comparative advantage of regions in international markets. Table 6 shows the change in the terms of trade due to knowledge diffusion. Given our Armington specification for international trade[30], changes in the terms of trade are rather small, even if different knowledge types are assumed to be perfect substitutes. As China receives the large knowledge spillovers relative to its existing capital stock, terms of trade changes are also the largest for China. Accordingly, the increase in China's share of total exports in the world market is the largest among all countries, but is relatively small with about 4-5.5%.

B. Knowledge Diffusion and the Costs of Climate Policy

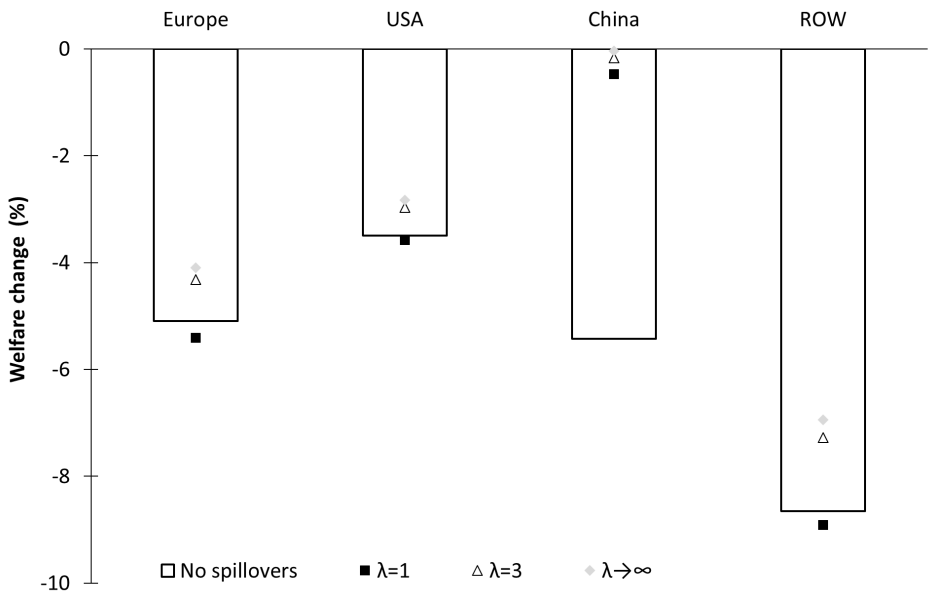
This section examines whether and how knowledge diffusion can reduce the cost of climate policy at both the global and regional level. We focus on a global carbon-pricing climate policy with a relatively aggressive environmental target, i.e., we assume that CO_2 emissions in 2050 are reduced by 50 percent relative to 2010.[31]

Due to the positive growth effects discussed in the previous Section III.A, CO_2 emissions are higher in a world with spillovers as compared to the "no spillovers" case. Moreover, emissions in the "no policy" cases depend on λ. To calculate how knowledge diffusion affects the cost of climate policy, we thus have to control

[30]Substitution elasticities for Armington aggregation are relatively low and, together with the share-preserving nature of the CES function, imply a relatively "tight" approach to modeling (changes in) international trade.

[31]While we do not attempt to analyze a specific climate policy proposal here, our choice for the global emissions reduction target is broadly in line with the current climate policy discussions. First, Nordhaus (2010) estimates that in order to limit the global temperature increase to 2°C above pre-industrial levels it is required to reduce global CO_2 emissions in 2050 (relative 2010) by about 40%. The comparable number from the *Fifth Assessment Report* of the IPCC (2014) suggests that reductions between 40-70% would be needed. Focusing on the 2°C target, our simulations are thus also relevant for the post-Paris world. Appendix B provides some further quantitative context by comparing our projections for emissions and carbon prices to the results from existing, comparable studies in the field.

FIGURE 4. Welfare impacts from climate policy with and without knowledge spillovers for different λ



Note: All scenarios achieve the same absolute amount of year-on-year global CO_2 emissions relative to the respective "no climate policy" baseline.

for the growth effects of knowledge diffusion in different baselines corresponding to different values for λ. For each value of λ, we can calculate the costs of climate policy. Comparing worlds with knowledge spillovers ($\lambda > 0$) to the one without spillovers ($\lambda = 0$) then allows us measure the impact of knowledge diffusion on the cost of climate policy. In addition, to ensure comparability across scenarios, we assume that all scenarios achieve the same *absolute amount of CO_2 emissions reductions* in each year. We can hence compare the cost-effectiveness of climate policy in light of different assumptions about knowledge spillovers. We further assume full trading of carbon permits between regions.[32]

Figure 4 shows the welfare impacts by region of the global climate policy in a world with and without knowledge spillovers, and for alternative assumptions about λ. Welfare costs for the ROW and China are the highest in the carbon policy scenario reflecting the fact that these regions bear the largest emissions reductions under a global carbon-pricing policy.[33] Comparing the costs of climate policy with and without knowledge spillovers shows cost reductions of more than 90% (or about 5 percentage points of welfare) for China. For other regions, whether costs are

[32]Our scenarios can thus be equivalently thought of as a global carbon tax which achieves the same year-on-year emissions reductions as the global cap-and-trade policy.

[33]Both China and the ROW are characterized by a relatively large number of abatement options with relatively low marginal costs. Equalizing marginal abatement costs globally hence shift large parts of the abatement to these regions whereas the lower substitutability between fossil fuels and non-carbon inputs in Europe and the US implies in general implies higher marginal abatement costs in the latter regions.

reduced or not depends on the degree of substitutability between different types of knowledge spillovers. If knowledge spillovers from different sources can be combined more effectively (i.e., $\lambda = 3$ and $\lambda \to \infty$), the welfare costs of climate policy decrease by up to 20%. If, however, the substitutability is limited ($\lambda = 1$), knowledge diffusion slightly increases the welfare costs of climate policy by up to 6%, 2%, 3% for Europe, the US and the ROW, respectively.

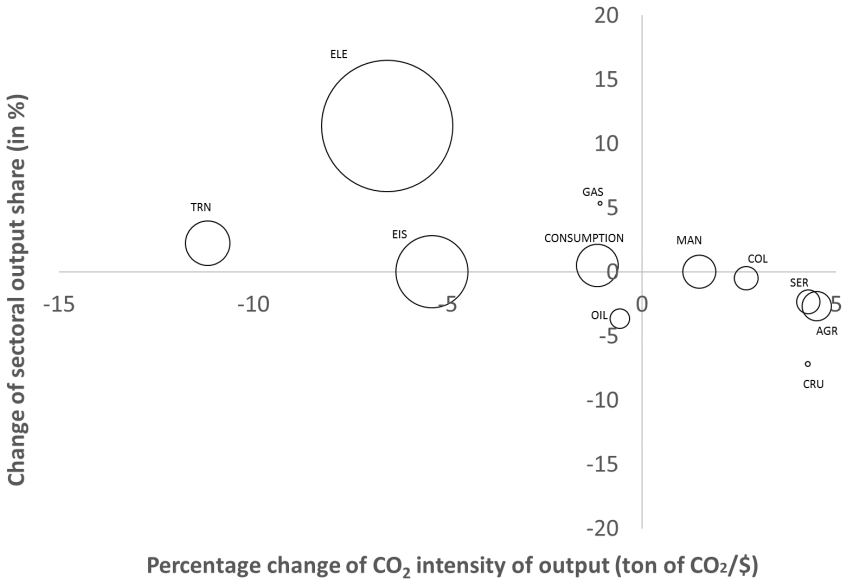
To understand why knowledge diffusion affects the welfare costs from climate policy differently across regions, it is instructive to look at how knowledge diffusion changes the carbon intensity of economies and the sectoral composition of output *in the absence of carbon policy*. First, knowledge spillovers increase CO_2 emissions in all regions as economies grow faster. For example, for $\lambda = 3$, emissions in 2050 increase by 3.5% for Europe, 4.6% for the USA, 16.8% for China, and 4.5% for the ROW relative to "no spillovers" emissions in year 2050. The emissions increase in China is the largest as knowledge diffusion leads to the highest increase in the growth rate of output for China. Second, higher emissions do not imply, however, a higher CO_2 intensity of output as knowledge diffusion brings about a change in the sectoral composition of output with changes towards a "greener" economy. For $\lambda = 3$, the emissions intensity of output (measured as tons of CO_2 per value of output) in year 2050 is reduced by 6.1% for Europe, 9.8% for the US, 4.8% for China, and 6.4% for the ROW.[34]

Figure 5 shows the underlying changes in the sectoral composition of output (on the vertical axis) for China and the USA that is brought about by knowledge diffusion (in the absence of climate policy). The horizontal axis shows the change in the emissions intensity of industry output while the size of bubbles indicates the share of CO_2 emissions by industry in economy-wide emissions in the "no spillovers" reference case. The reduction in the overall carbon intensity due to knowledge diffusion is the larger, the more of the industries that account for large emission shares reduce either their CO_2 intensity or their share in total output (or ideally a combination of both). Figure 5 shows that knowledge diffusion indeed spurs industry dynamics that lead a to lower emissions intensities in both regions. This "greening" of the economy is much more pronounced in China as compared to the USA as the knowledge diffusion adds more knowledge relative to the existing capital stock for China (see the discussion in Section III.A). It is also apparent that with $\lambda = 1$, relatively little structural change is brought about by knowledge diffusion in the US economy (i.e., the black solid bubbles mostly cluster around the origin).

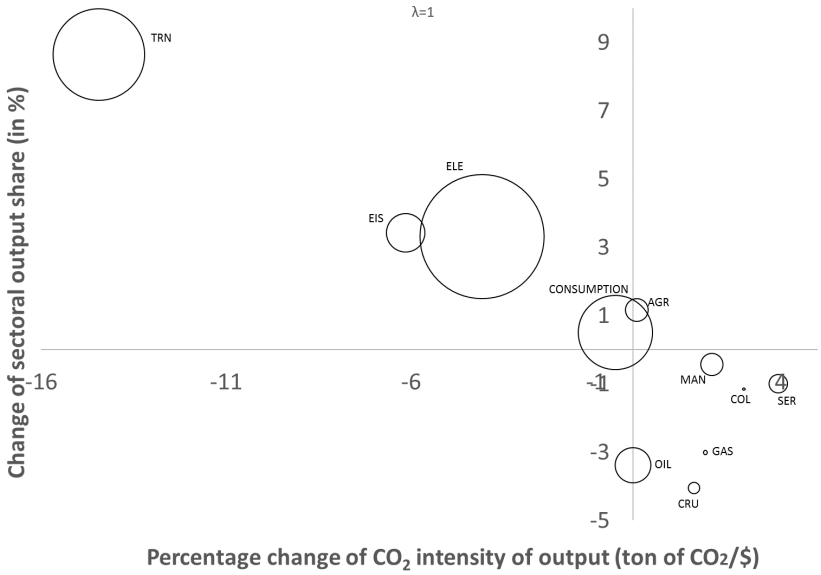
Knowledge diffusion leads to a "greener" economy because the sectors with relatively low carbon intensities tend to be the sectors which are (1) relatively knowledge-intensive and (2) comprise a large share of economy-wide output. If spillover coefficients, both for the international and domestic knowledge diffusion channel, would be identical across sectors, (1) and (2) imply that larger *flows* of knowledge are gener-

[34]The decline in the emissions intensity in 2050 due to climate policy (assuming $\lambda = 3$) is 54% for Europe, 56% for the USA, 38% for China, and 56% for ROW. Given the stringent climate policy assumed here, a simple decomposition would thus attribute the most part of the change in the emissions intensity to the carbon price (about 90% for Europe with similar numbers for the other regions).

FIGURE 5. Impact of knowledge spillovers on industry composition of total output and industry-level CO_2 emissions intensity



(a) China



(b) USA

Notes: Size of bubbles show the share of CO_2 emissions by industry in economy-wide emissions in the "no spillovers" reference case. Changes for variables on horizontal and vertical axes refer to the year 2050 comparing a world with spillovers to the "no spillovers" reference case. Results for Europe and the ROW are qualitatively similar and thus not shown here. Case shown assumes $\lambda = 1$.

ated for sectors with low carbon intensities. This in turn increases the productivity of these sectors and reduces production costs. As a result, their share in total output increases. Even if spillover coefficients are not identical across sectors—as is in fact borne out by our empirical estimation—this size effect dominates potential differences in sectoral impacts that may result from differences in sector-specific spillover intensities. Moreover, as knowledge diffusion tends to increase more strongly the productivity of industries with a relatively low energy- (and CO_2-) intensity, it effectively increases the relative price of energy goods. This triggers a substitution away from energy (and CO_2) towards inputs with a low (or zero) carbon content, and hence explains the decline in the CO_2 intensity of most industries.

Only if the "greening" effect from knowledge diffusion is sufficiently strong, the costs of climate policy are reduced. An overall lower carbon intensity and higher productivity of sectors, in particular for those with relatively low carbon intensities reduces the costs of climate policy for four reasons. First, for a given CO_2 price and a given substitutability between inputs in production, a lower cost share of carbon implies lower costs. Second, a higher productivity of energy-intensive sectors means that less energy is needed to produce the same amount of output. Third, the carbon policy shift resources to non-energy sectors, which have become more productive with knowledge diffusion (as compared to a world without knowledge diffusion). Fourth, knowledge diffusion improves the comparative advantage for regions that export "clean" (i.e., low carbon) goods which increases gains from trade with positive impacts on welfare (thus contributing to a reduction of welfare losses from climate policy).

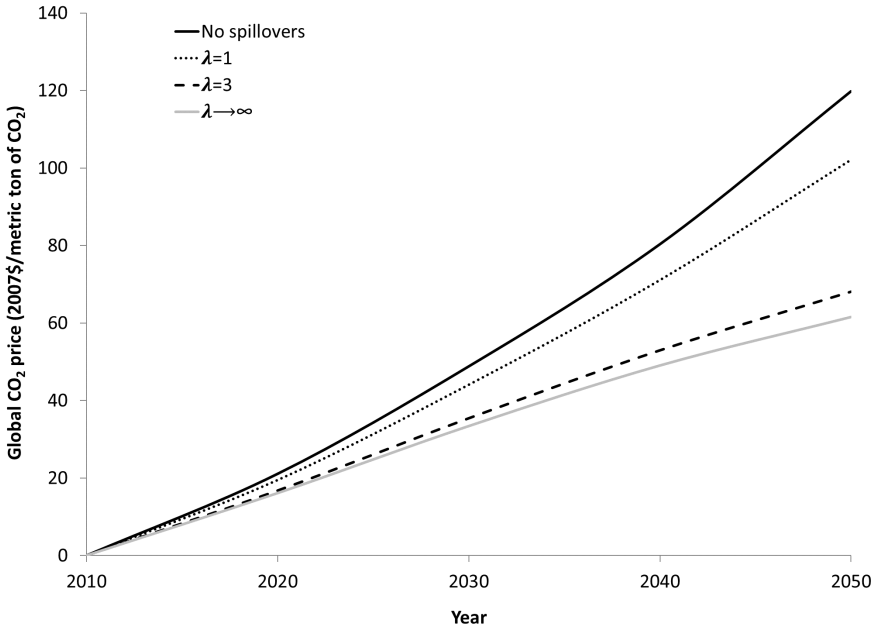
In summary, as the knowledge increase relative to existing knowledge without spillovers is by far the largest for China, its welfare cost of climate policy is reduced significantly. For other regions, the "greening" effect is much weaker, and only produces small reductions in welfare costs if different types of knowledge spillovers are strong enough substitutes (i.e., $\lambda > 3$).

Figure 6 shows that assessing the impacts of climate policy in a world with or without knowledge diffusion has drastic implications for carbon prices. For the same quantity of CO_2 emissions reduced, the carbon price in year 2050 for $\lambda = 1$ ($\lambda \to \infty$) is 15 (49) percent lower with knowledge diffusion as compared to a world without knowledge diffusion. This underscores the importance of sharing knowledge for limiting the costs of global climate policy.

C. Sensitivity Analysis

Here we consider the sensitivity of results to parameters affecting how knowledge diffusion affects regional and sectoral changes in productivity and in turn the welfare costs of climate policy. We explore the extent to which welfare costs depend on the substitutability between foreign and domestic goods and the ease with which carbon-intensive energy can be substituted for non-energy inputs in production and consumption. Finally, we investigate the role of endogenous growth in lowering welfare costs of climate policy in the presence of knowledge diffusion. Here, we

FIGURE 6. Global CO_2 price under climate policy with and without knowledge spillovers for different λ



Note: All carbon price trajectories achieve the same absolute amount of year-on-year global CO_2 emissions relative to the respective "no climate policy" baseline.

contrast a formulation of our model in which the long-run growth rate is exogenous with endogenous growth specifications based on alternative assumptions about the extent of gains from specialization at the sectoral level.

TRADE ELASTICITIES.—The extent to which knowledge diffusion affects the costs of climate policy could well be affected by how sensitive international trade pattern react to productivity and price changes. As knowledge diffusion affects the relative productivity between regions and sectors, it can improve or negatively affect the international competitiveness of trade-exposed industries. To explore this possibility, we performed sensitivity analysis with respect to the Armington elasticity parameters considering two additional "low" and "high" scenarios which assume that central cases parameter values are halved and doubled, respectively.

We find that our results are not much affected (see Table 7). Lowering (increasing) elasticities only very slightly decreases (increases) welfare gains from knowledge diffusion if no climate policy is present. For a given economy, higher elasticities increase the demand for imported goods, resulting in increased exports of other regions. The expansion of the production in foreign regions boosts investment and innovation leading to larger knowledge stocks. This in turn implies larger knowledge spillovers for the domestic economy whose positive effects are propagated through international trade. Quantitatively, and relative to our central case parametrization, these effects are, however, negligible.

TABLE 7. Sensitivity of change in costs of climate policy due to knowledge diffusion[a]

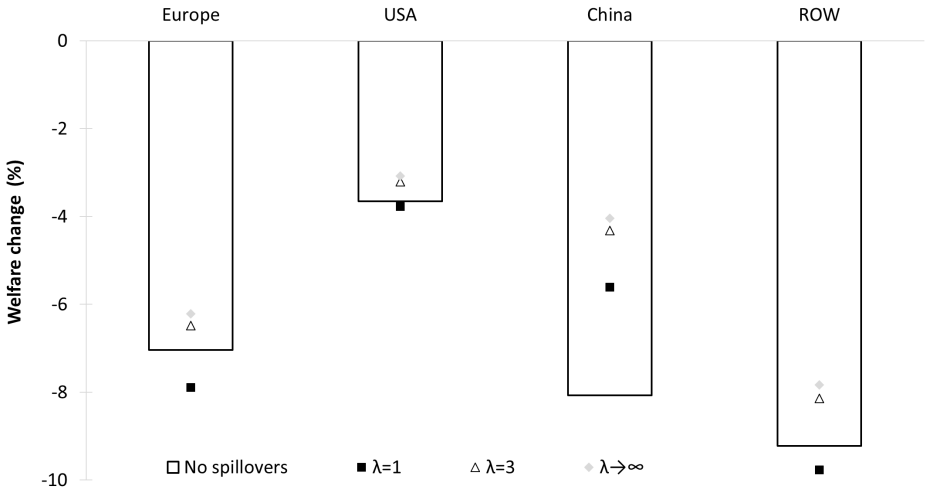
	Europe		USA		China		ROW	
Central case	-15		-15		-97		-16	
Alternative cases								
	low	high	low	high	low	high	low	high
Production parameters[b]								
γ	-2	-30	-1	-30	-106	-79	-5	-30
ν	6	-35	3	-27	-174	-54	0	-28
Consumption parameters[b]								
σ_{ec}	-15	-16	-15	-16	-108	-84	-16	-17
σ_c	-15	-16	-15	-15	-97	-97	-16	-16
Trade parameters[b]								
η	-15	-17	-15	-17	-86	-126	-16	-16
Growth (variety) parameter[c]								
Markup $(1-\kappa)$	9	-30	9	-30	-46	-95	7	-31

Notes:
[a] All figures refer to percentage change of welfare costs relative to a "no climate policy" baseline assuming $\lambda = 3$.
[b] "low" ("high") case assumes that parameters are halved (doubled) relative to the respective central case parameter value.
[c] "low" case assumes that mark-up is zero in line with an exogenous growth model; "high" case assumes a mark-up of 20% over marginal costs (central case value is 14%).

ELASTICITIES OF SUBSTITUTION IN PRODUCTION AND CONSUMPTION.—We find that degree of substitutability between energy and non-energy inputs in production has a relatively large impact for the change in costs of climate policy brought about by knowledge diffusion (Table 7). With low elasticity of substitution between Q and inputs from other sectors (γ) and low elasticity of substitution between energy and labor ν, the cost reduction for China is larger and for the other countries smaller than in the central case. While for all countries a lower γ or ν makes it harder to substitute away from energy which becomes more costly under a climate policy, China is better off due to the large knowledge inflows relative to other countries. This boosts productivity and lowers the cost of producing goods in China by more than in other countries. As a result, China gains market shares by increasing its exports while other countries increase their imports. For low values of γ or ν, the loss in market shares and ensuing negative impacts on welfare for Europe, USA, and the ROW in fact imply that knowledge diffusion slightly increases the costs of climate policy. For high substitution elasticities, knowledge diffusion leads to a smaller increase in the comparative advantage of Chinese exports thereby resulting in smaller reductions in welfare costs of climate policy for China, and in larger cost reductions for Europe, USA, and the ROW.

We find that changing elasticities of substitution in consumption between energy and non-energy goods (σ_{ec}) and between non-energy goods (σ_c) does have only

FIGURE 7. Welfare impacts from climate policy with and without knowledge spillovers for different λ and assuming that carbon revenues are retained in each region



Note: All scenarios achieve the same absolute amount of year-on-year global CO_2 emissions relative to the respective "no climate policy" baseline.

negligible quantitative effects.

ENDOGENOUS GROWTH.—Lastly, we examine the interplay between knowledge diffusion and endogenous growth. We vary the markup parameter κ in (4) which reflects the substitutability between different varieties in the production of sectoral outputs or, alternatively, the market power of monopolistic producers. A higher market power means that firms are able to charge a higher markup ($= 1 - \kappa$) over marginal costs, in turn implying larger incentives for specialization driving endogenous growth. By setting $\kappa = 1$, the markup is zero, and hence our model collapses to a standard exogenous growth model (Ramsey, 1928). In this case, knowledge diffusion still alters the costs of climate policy but to a much smaller extent than in the central case: it lowers costs for China and slightly increases the costs of other countries as, again, these latter countries become less competitive on international export markets. For higher markups the effects of knowledge diffusion are magnified resulting in about twice as large cost reductions for Europe, USA, and the ROW. This is simply because higher markups imply that more knowledge is accumulated which can be shared through knowledge diffusion. This underscores the importance of investigating knowledge diffusion in a setup that represents an endogenous mechanism for accumulating knowledge over time.

REGIONAL DISTRIBUTION OF CARBON TAX REVENUES.—We have assumed so far that carbon revenues are returned lump-sum to regions in proportion to their historic (i.e., year 2010) CO_2 emissions. After the Paris agreement, unilateral climate policies may be viewed as more viable than a global carbon pricing policy. Under such a setting, the carbon revenues would be fully retained in each region. We have thus

also examined a scenario which considers unilateral mitigation efforts to reach a 50% reduction in global emissions by 2050. While this, not surprisingly, changes the regional costs of carbon mitigation, we find that the impacts of knowledge diffusion on the cost of climate policy are quantitatively similar and qualitatively identical.

Figure 7 shows the case of unilateral climate policies which fully retain the carbon revenues within each region. Comparing with Figure 4 shows that results under unilateral climate policies are largely similar—with the exception for China. China has higher welfare costs under unilateral policy as compared to global carbon pricing as with global carbon pricing China benefits from supplying relatively cheap abatement options to the international carbon market (hence obtaining large revenues from international permit trade relative to the cost of emissions reduction). Importantly, however, knowledge diffusion brings about a similar reduction of welfare costs in terms of percentage points under both ways of distributing the tax revenues.[35]

IV. Conclusion

This paper has introduced domestic and international knowledge diffusion at a sectoral and regional level in an endogenous growth model. Knowledge diffusion depends on accessibility and absorptive capacity; we have empirically estimated these processes using patent and citation data to inform parametrization of our numerical general equilibrium model. The sectoral and regional detail of the model allowed us to examine the impacts of knowledge diffusion, through size and competition effects, on economic growth and the costs for global climate policy.

Importantly, we find that knowledge diffusion leads to a "greening" of economies that is characterized by increased market shares of "clean" carbon-extensive sectors and lower sectoral (and economy-wide) emissions intensities. "Clean" sectors with relatively low carbon intensities exhibit high knowledge capital intensities, implying a large absorptive capacity. Knowledge diffusion thus boosts the productivity of these "clean" (non-energy) sectors by more than it does for "dirty" (energy) sectors. This, in turn, decreases the production costs of "clean" relative to "dirty" goods. When energy (carbon) inputs become more expensive under a climate policy regime, the costs of substituting away from carbon-intensive goods are lowered because "clean" goods can be produced at lower costs.

The "greening" effect has the potential to substantially lower the costs for global carbon mitigation policies. We found that for regions with relatively little own knowledge (e.g., China), reductions in policy costs can be up to 90%. For developed regions (e.g., Europe and the U.S.), policy costs can decrease but also increase

[35] To see this, note that without knowledge diffusion, welfare costs for China are (1a) 5.4% when tax revenues are rebated based on historical emissions, and (2a) 8.1% when the revenues are kept in each region. With knowledge diffusion, the welfare costs are between (1b) 0-0.5% when tax revenues are rebated based on historical emissions and (2b) between 4.0%-5.6% when revenues are kept in each region. Thus, the welfare costs of climate policy are reduced by 4.9-5.4 percentage points (1b minus 1a) when revenues are distributed based on historic emissions and by 2.5-4.1 percentage points (2b minus 2a) when revenues are kept in each region.

depending on the strength of the "greening" effect. If the substitutability between different types of knowledge is high, costs are reduced by up to 20%, while the costs slightly increase when the substitutability is relatively low. A simple but important implication of our analysis is that in order to control emissions, carbon pricing policies should be complemented by R&D policies aimed at promoting knowledge diffusion. The impacts of knowledge spillovers on economic growth are substantial corresponding to welfare gains for the global economy of about 4-10% depending on the substitutability between different types of knowledge (spillovers).

Our paper is a first step toward a comprehensive framework that can be used for the analysis of environmental regulation in the context of domestic and international knowledge diffusion with endogenous technology. Several directions for future research appear fruitful. First, it would be interesting to study a differentiate between a larger number of world regions to obtain more detailed regional results. Second, the presented framework could be used to analyze more explicitly the role of R&D policy providing economic incentives for sharing knowledge internationally. Third, a particularly interesting direction is to discuss the issue of policy coordination between climate and energy policy and R&D policy. For example, given that the knowledge diffusion seems to benefit mainly China, Europe and the US may be reluctant to approve regulations which allow more knowledge diffusion to China or may ask in exchange China for doing more emissions reductions. Finally, another line of important future research would be to include renewable energy technologies. This would enable examining knowledge diffusion processes for clean energy and the interactions with climate policies in a carbon-constrained world.

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Appendix A: Additional tables

Table A1. Estimated knowledge accessibility parameters

Panel (a): Knowledge accessibility parameters ϕ^b_{hir}

	Sector				
	AGR	EIS	ELE	MAN	TRN
Europe					
AGR	0	0.11	0	0	0
EIS	0.95	0	0.6	0.29	0.67
ELE	0	0.25	0	0.16	0.19
MAN	0.01	0.04	0.1	0	0.14
TRN	0.05	0.6	0.3	0.55	0
USA					
AGR	0	0.12	0	0.01	0
EIS	0.95	0	0.53	0.28	0.62
ELE	0	0.24	0	0.13	0.15
MAN	0.01	0.07	0.12	0	0.22
TRN	0.03	0.58	0.36	0.57	0
China					
AGR	0	0	0	0	0.59
EIS	0	0.31	0	0	0.09
ELE	0	0	0	0	0.32
MAN	0	0.69	1	1	0
TRN	0	0	0	0	0
ROW					
AGR	0	0.05	0	0	0
EIS	1	0	0.4	0.19	0.66
ELE	0	0.23	0	0.16	0.03
MAN	0	0	0.11	0	0.31
TRN	0	0.71	0.48	0.66	0

Panel (b): Knowledge accessibility parameters ϕ^c_{irs}

	Region			
	Europe	USA	China	ROW
Europe				
AGR	–	0.28	0.09	0.31
EIS	–	0.32	0.07	0.37
ELE	–	0.26	0.12	0.27
MAN	–	0.31	0.11	0.28
TRN	–	0.30	0.09	0.22
USA				
AGR	0.19	–	0.22	0.55
EIS	0.18	–	0.08	0.34
ELE	0.19	–	0.15	0.37
MAN	0.17	–	0.11	0.31
TRN	0.19	–	0.12	0.27
China				
AGR	0.22	0.08	–	0.13
EIS	0.18	0.10	–	0.29
ELE	0.17	0.11	–	0.35
MAN	0.17	0.13	–	0.41
TRN	0.14	0.10	–	0.51
USA				
AGR	0.59	0.65	0.69	–
EIS	0.64	0.57	0.85	–
ELE	0.64	0.63	0.73	–
MAN	0.66	0.57	0.77	–
TRN	0.68	0.60	0.80	–

Notes: Due to data availability, we have to make assumptions on the accessibility intensity of sectors for which there is no patent data. We thus assume that energy sectors (coal, crude oil, refined oil and gas) have the same intensity as the energy intensive sector.

Table A2. Lists of model parameters and values

Parameter	Description	Value
Elasticity of substitution parameters		
γ_{ir}	Substitution between Q and inputs from other sectors B	0.5
ν_{ir}	Substitution between energy E and labor L	1
ω_{ir}	Substitution between energy types in energy aggregate production	0.5
η_{ir}	Substitution between domestic goods and imports (varies by good)	1.9–6
ψ_{ir}	Substitution between imports from different regions	3.8–12
n	Substitution between sectoral goods in aggregate consumption	0.25
σ_u	Substitution between sectoral goods in final demand u	0.3–0.5
κ	Measurement of elasticity of substitution between varieties	0.86
$1/\theta$	Intertemporal elasticity of substitution	0.5
Other parameters		
α_{ir}	Share of intermediate composite in final good production	0.19–0.70
ϕ_{ir}	Share of labor in intermediate good production	0.01–0.83
ϑ_{kir}	Share of fuel sources in energy aggregate production	0–0.97
ζ_{ir}	Share of domestic product in armington good aggregate	0.13–1
m_{isr}	Share of import from region s to r in import aggregate of region r	0–1
δ_0	Depreciation rate of capital at time 0	0.07
$\bar{r}$	Default interest rate	0.05
c_{ir}	Cost share of sectoral goods in consumption	0.01–0.75
$\theta^u_{i'ir}$	Cost share of goods i' in the production of final demand category u in sector i	0.01–0.75

Notes: Values for elasticity of substitution parameters in production and consumption are taken from Paltsev et al. (2005). The value for the IES in utility is based on Hasanov (2007). The remaining parameters are taken from Narayanan, Badri and McDougall (2012). Values for the cost share parameters beyond the value ranges shown above are available on request from the authors.

Appendix B: Comparing CO_2 emissions and carbon prices with results from other studies

This appendix compares our simulation results for CO_2 emissions and carbon prices from our model to the findings from other comparable studies in the field. For reference, we include here results from the Nordhaus (2010) and the *Fifth Assessment Report* by IPCC (2014). As a general caveat, it should be clear that such a comparison across models is inherently difficult due differences in methodology, data, modeling assumptions, and scenario definition. In particular, none of the mentioned studies does consider knowledge diffusion—which means that we can only compare to the central case results from our model that assumes no knowledge diffusion (i.e., $\lambda = 0$). The rationale behind comparing results from different studies is rather to provide some quantitative context about the baseline and policy-induced paths of CO_2 emissions and carbon prices, illustrating that our model produces results that are consistent with those from other analyses.

Table B1 summarizes the main findings from this comparison. It is apparent that for the case without knowledge diffusion—and thus corresponding to the case implicitly contained in the existing literature—our simulations are quantitatively consistent in terms of projected paths for emissions and the global carbon price.

Table B1. Cross-study comparison of global CO_2 emissions and carbon prices without and with climate policy

No climate policy		Climate policy		
CO_2 emissions (Gt) in year			Absolute emissions	Global CO_2 price in year 2050
2010	2050	2050	reduction 2010-2050	(2007$/metric ton of CO_2)
This study (central case assuming no knowledge diffusion, $\lambda = 0$)				
29.8	75.1	14.9	14.9[a]	120
Other studies				
5th Assessment Report (IPCC, 2014)[b]				
30.0–37.5	43.3–73.1	11.3–18.0	12.0–26.2	97–247
Nordhaus (2010)[c]				
29.7	55.1	18.3	11.4	119

Notes:
[a]Recall that in order to investigate the impacts of alternative assumptions about knowledge diffusion for the cost of climate policy, we hold fixed the absolute amount of emissions reductions.
[b]Emssions values are based on Figure 3.2 in IPCC (2014), showing 40%-70% emission reduction in 2050 relative to 2010. CO_2 prices (in 2010$) are taken from the 450ppm scenario and are compiled from supplementary online data sources underlying the IPCC (2014) report.
[c]Emissions values are based on the scenario labeled "Limit T < 2°C" in Figure 1 from Nordhaus (2010), and converted from carbon to CO_2. The global carbon price is taken from the same scenario is expressed in 2005$.