Justus-Liebig University Giessen
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Four Essays on Climate, Energy, and Sports Economics

Doctoral Thesis

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Submitted on: April 19, 2018
Defended on: December 18, 2018

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For Laura and Oscar

Acknowledgements

This dissertation was written while I was employed as research and teaching assistant at the Chair for International Economics (VWL III) at the the Department of Economics and Business Studies of the Justus-Liebig University Giessen. In parallel, I have been a researcher at the Frankfurt School - UNEP Collaborating Centre for Climate and Sustainable Energy Finance situated at the Frankfurt School of Finance and Management. I was very lucky to have a supervisor at each institution, Prof. Dr. Jürgen Meckl at Giessen University and Prof. Dr. Ulf Moslener at Frankfurt School, who both supported me throughout the dissertation. I would like to thank Prof. Dr. Jürgen Meckl for giving me the opportunity to write my dissertation in the first place and Prof. Dr. Ulf Moslener for offering me a position at the FS - UNEP Centre, which proved very fruitful for my thesis, but also for my budget constraint. I am grateful that both my supervisors were always open to my diverse research ideas and for their guidance and very constructive comments and recommendations.

This doctoral thesis also includes joint papers with other co-authors, namely with Christian Haas and Dr. Hannes Rusch. I would like to thank both of them for the very constructive and rewarding cooperation. Furthermore, I thank my former colleagues at Giessen University. I am grateful for all new friendships, critical discussions, and conversations.

Last but not least, I would like to thank my family, my parents and my two sisters, as well as my friends. Although their support for my work on this thesis was rather indirect, it should not be underestimated. You always had my back and made sure that I stay on track. Most of all, I owe my thanks to the outstanding support of my wife Laura. I thank her for her proofreading and, more importantly, raise my hat to her ability to always motivate me whenever I had any doubts or setbacks.

Chapter 1

Introduction

This dissertation consists of two main parts with different themes that are analysed in two papers, respectively. The first part consists of theoretical analyses of topics in the area of energy and climate economics. Climate change caused by greenhouse gas emissions is one of the greatest (economic) challenges of our time. Limiting global warming requires an understanding of the interaction between economic activity, energy use, emissions, and energy-saving/clean technologies. In particular, knowing the underlying market failures that prevent the first-best outcome is a prerequisite for designing and implementing effective and efficient policy instruments.

The paper "*Climate Policy with the Chequebook – An Economic Analysis of Climate Investment Support*" (Chapter 2), co-authored with Ulf Moslener, identifies and characterises main market failures related to climate mitigation investments, in particular clean energy, and discusses recent trends in international climate policy, which seems to have shifted from debating emission targets towards financing commitments. This paper first characterises investment support instruments, such as grants, concessional loans, and guarantees, that are increasingly being used in national and international climate policy to promote clean energy investments. In order to assess these instruments, we then turn to investigation clean energy investments and stress the role of capital market imperfections, in addition to the typically analysed market failures, i.e. emission externalities and innovation spillovers. We analyse their negative impacts on the risk-return characteristics of these investments. While investment support instruments are able to address negative impacts of these market failures, they are not always the first-best solution. Such instruments can effectively compensate capital market imperfections and innovation spillovers if designed appropriately. However, we argue that financial instruments are in general inferior to marked-based instruments in compensating for emission externalities and thus should only be used if an emission price is (politically) not feasible. Based on our analysis, the paper provides policy recommendations on the choice of finance instruments to address the identified market failures as well as guidance on how to use these instruments in order to reduce the risk of inefficient public spending.

The second paper "*Directed Technical Change and Energy Intensity Dynamics: Structural Change vs. Energy Efficiency*" (Chapter 3), co-authored with Christian Haas, investigates another promising way to reduce emissions and thus meet climate policy targets: reducing the energy used to produce a certain level of output, i.e. decreasing energy intensity in the economy. This paper investigates two core drivers of energy intensity reductions: the adoption of more efficient production technologies and the adjustments of the structural composition of economic activity. The contribution of both driving forces to energy intensity reductions substantially differs across economies. Using a model with directed technical change, this paper provides new insights on the effects of energy price growth and endogenous technical change on energy intensity developments. We decompose changes in aggregate energy intensity into structural changes in the economy (*structural effect*) and within-sector energy efficiency improvements (*efficiency effect*). We find that both sectoral productivities that drive the direction of technical change and energy price growth determine the direction and magnitude of both effects. The *efficiency effect* dominates the development of energy intensity in economies, where research is directed to the energy-intensive sector. When research is directed to the labour-intensive sector, the *structural effect* is the main driver of energy intensity dynamics. In both cases, increasing energy prices cause reductions in energy intensity by inducing a substitution of energy by other factors of production. Energy price shocks might induce a permanent redirection of innovation activities. In order to illustrate the results and to cross-check our findings with empirical decomposition studies, we calibrate the model to empirical data. Our simulation results for 26 OECD countries are largely consistent with the empirical evidence.

The second part of this doctoral thesis addresses labour market issues that are empirically analysed based on professional sports data. Professional sports provides a unique laboratory for labour market research. One advantage is the detailed and accurate information on attributes, performance, and earnings of individuals. Furthermore, individuals' actions within sports contests are observable and well documented, which offers a unique setting to study behaviour.

The paper "*Misconduct and Leader Behaviour in Contests – New Evidence from European Football*" (Chapter 4), co-authored with Hannes Rusch, provides an empirical investigation of severe misconducts in contests. Misconduct is either illegal or immoral behaviour and thus committed covertly in many economic contests. Professional sports offers the opportunity to investigate such behaviour, as destructive actions against the opponent can be observed openly and rather reliably. Using data from European football championships, we extend previous literature by differentiating between two types of misconduct both resulting in a yellow card, namely dissents against the authority in charge of the interpretation and enforcement of the contest's rules, i.e. the referee, and other misconducts aimed at the opposing team directly, i.e. fouls. For other misconducts we find that teams with lower ability are more likely to commit sabotage in order to compensate for their disadvantage. Sabotage is also more likely when the outcome of the contest is still open. In contrast to sabotage, dissent with the referee is affected by the current score of the match. The more unfavourable the score is, the more likely is dissent with the referee. This finding could indicate self-serving (or team-serving) attribution. Another new perspective we introduce is the differentiation between misconducts committed by team captains and other players. Our findings indicate that captains challenge referees' decisions in direct reaction to sanctions awarded to teammates. Furthermore, they engage in more misconduct during important matches, while retaliative foul plays cannot be observed for captains. Finally, our analyses indicate that all types of misconduct have a negative effect on the likelihood of team success. As we find that (severe) punishment seems to deter misconducts, it could be a possible measure to prevent or at least reduce illegal behaviour in contests. This measure is also applicable to other contests (e.g. within firms) as long as punishment can be observed by other team members.

Finally, the paper "*Generalists vs. Specialists: Skill Variety and Remuneration in Football*" (Chapter 5) uses professional sports data from the German *Bundesliga* to analyse the returns on skill variety and extends the existing literature on the remuneration of generalists versus specialists. To the best of my knowledge, it is the first contribution that measures skill specialisation based on the concept of task-specific human capital. The main idea is that task-specific human capital is accumulated on the job through learning-by-doing. The basic idea is as follows. The more an employee focuses on one or very few tasks, the higher is his specific human capital and thus productivity in that task(s), i.e. he is a specialist. An individual, who has performed a larger variety of different tasks, but each of them less often than the aforementioned specialist (given the same level of work experience), would have a more versatile task-specific skill set and thus could be referred to as a generalist. A specific advantage of football data for analysing this issue is that it allows for a precise measurement of specialisation of players in certain skills/tasks. In football, there are three main field positions – defender, midfielder, and forward – that I refer to different occupations in a football team (firm). These can be further subdivided into twelve tactical (sub-)positions[1], which could be interpreted as specific tasks in team production. To measure whether a player is rather a specialist or a generalist, I construct three measures of skill specialisation. The empirical findings indicate that returns to skill specialisation are occupation-specific: defenders and forwards receive a return on skill specialisation, while midfielders neither benefit from specialisation nor receive any premium for being generalists. An explanation might be that defenders and forwards have more specialised tasks in football compared to midfielders. While the latter are almost equally engaged in offensive and defensive plays, the former two groups mainly perform defensive or offensive tasks. Hence, it is not surprising that forwards and defenders earn a premium as specialists. In the general labour market context, these findings indicate that specialisation seems to be a more beneficial strategy for employees. Particularly in occupations characterised by a specific and narrow set of tasks, there are salary premiums on specialisation, while there is no effect of skill versatility even in occupations involving a wider range of tasks.

All four papers are separate works and presented as such. As the first two papers are already published, they are included in the layout of the respective journals. The third and fourth paper are unpublished working papers.

[1]These positions are Left-, right-, and centre-back; left-, right-, defensive-, central-, and attacking midfield; left-, right wing, secondary striker, and central forward.

Chapter 2

Climate Policy with the Chequebook – An Economic Analysis of Climate Investment Support

Reference for this Paper:

Kempa, Karol and Ulf Moslener (2017), "Climate Policy with the Chequebook – An Economic Analysis of Climate Investment Support", *Economics of Energy & Environmental Policy* 6(1), 111-129. DOI: 10.5547/2160-5890.6.1.kkem.

Conferences with Review Process:

12th European Conference of the International Associations for Energy Economics, Venice, 2012 (presentation by Ulf Moslener).

Climate policy with the chequebook— An economic analysis of climate investment support

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ABSTRACT

Across the globe, climate policy is increasingly using investment support instruments, such as grants, concessional loans, and guarantees—whereas carbon prices are losing importance. This development substantially increases the risk of inefficient public spending. In this paper, we examine the ability of finance instruments to effectively and efficiently address market failures related to clean energy investments. We characterise these market imperfections—emission externalities, knowledge spillovers and capital market imperfections—and identify their negative impacts on the investor-relevant risk-return characteristics. We argue that finance instruments are able to address the effects of these market failures. However, a carbon price is superior in internalising the emission externalities. With respect to the latter two inefficiencies, investment support instruments can effectively compensate the market failures if designed appropriately. We further provide policy recommendations on the choice of finance instruments to address the various market failures and guidance on how to use these instruments avoiding inefficient government spending.

Keywords: climate finance, investment support, market failures, policy instruments

https://doi.org/10.5547/2160-5890.6.1.kkem

1. INTRODUCTION—IS CLIMATE POLICY STILL ON TRACK?

Over the past few years, climate related policy intervention has witnessed a stark increase in the use of government subsidised financing. The corresponding instruments are neither directly tied to the emissions abated nor do they make carbon emissions more costly, but rather decrease the financing costs of certain projects and thereby increase the attractiveness of the corresponding investment. Essentially, the government moves away from its role as regulator determining the market rules and tackling externalities at their origin by introducing prices through carbon taxes or permit trading schemes. Governments take on the role of an actor on financial markets by providing financing to specific projects or programmes, often through their public finance institutions.

Environmental regulation and in particular climate policy have been through a dynamic history. Traditional command and control instruments dominated early policies characterised by government-defined technological standards such as "best available technologies" or direct

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Economics of Energy & Environmental Policy, Vol. 6, No. 1.

input or output controls (Harrington and Morgenstern, 2007). The economic literature following the work of Pigou (1920) powerfully demonstrated the superiority of market-based instruments—at least in terms of their ability to implement a given level of emissions at least cost.[1] One key issue is the decentralised nature of those market-based instruments that allows for cost efficient implementation without requiring detailed knowledge at the government level of technologies and individual firms' abatement cost structures. Rather than giving explicit directives on pollution levels, market-based instruments provide incentives through market signals to encourage the behaviour. These instruments—if designed and applied appropriately—realise a desired level of pollution abatement at least cost to society (Baumol and Oates, 1988; Montgomery, 1972; Tietenberg, 1995). The price signal induces an equalisation of marginal abatement costs across firms such that the pollution abatement burden is allocated efficiently among polluters, where firms with the lowest abatement cost will be the first to abate. Furthermore, market-based instruments perform better in terms of incentivising the development of new technologies which has led to a rapid increase in the use of these instruments since the 1970s across OECD countries (Hahn and Stavins, 1992; Jaffe and Stavins, 1995; Stavins, 2003; OECD, 1999). The most prominent economic instruments in climate policy are the CO_2 emissions trading scheme introduced by the European Union (EU) and the state-level emissions trading foreseen in the Kyoto Protocol to the United Nations Framework Convention on Climate Change in 2005 or 2009, respectively. Other policy schemes were introduced in parallel that mainly target the promotion of renewable energy (Menanteau et al., 2003).

In very recent years the trend of increased climate related government investment subsidy appeared, mainly through grants, interest subsidised loans or (less often) guarantees. Even the use of more complex so-called structured investment vehicles can be observed.[2] The EU recently set regulations on the use of financial instruments of various European funds for, among other goals, reducing pollution.[3] The International Development Finance Club (IDFC)—consisting of 20 national development banks operating nationally and internationally, inside and outside the OECD—reports total green financing by 18 reporting institutions of USD 99 billion in 2013 (Khosla et al., 2014). Multilateral Development Banks—not included in the figures above—report USD 28 billion of climate finance in 2014 compared to USD 27 billion in 2011 (World Bank, 2015). In addition to these financial institutions, 22 multilateral and 6 bilateral funds are dedicated to financing climate related investments.[4] According to the IEA/IRENA Global Renewable Energy Policies and Measures database, currently 208 support policies (subsidy and loan programmes) for renewable energy are in force worldwide.[5]

Consistent with this development, the international climate policy debate drifted from "emission targets" towards "financing commitments." A major element of the United Nations (UN) climate process is the promise of the industrialised countries to mobilise climate financing of USD 100 billion per year from 2020 on, to finance mitigation and adaptation in

1. See Sumner, Bird, and Dobos (2011) for a review of carbon tax policies.
2. An example is the *Global Climate Partnership Fund*, structured similarly to a credit default obligation (CDO) where the riskiest tranche is held by the government and serves as a risk buffer to attract private investment for the less risky tranches.
3. See EU Regulations No 1303/2013 and No 480/2014 as well as the Commission Implementing Regulation No 821/2014.
4. See Climate Funds Update, available at http://www.climatefundsupdate.org/ (last accessed 22 March, 2016).
5. The database is available at http://www.iea.org/policiesandmeasures/renewableenergy/ (last accessed 22 March, 2016).

developing countries (UNFCCC, 2012) and the establishment of the UN Green Climate Fund (GCF) by the Conference of the Parties (COP) in Durban (2011).

Thus, policy seems to move away from the explicit internalisation of externalities, it requires technology-specific information to formulate the investment subsidy programmes, and, by subsidising individual projects, it moves away from a decentralised approach. Considerations from a political economy perspective might explain parts of this trend. For a policy maker it is more attractive to offer support for climate friendly investments than to introduce additional costs for established conventional technologies (Bowen, 2011; Green and Yatchew, 2012). Green and Yatchew (2012) provide an economic analysis of support schemes focusing on the difference between programmes focusing on prices, e.g. feed-in tariffs, and quantities, e.g. renewable portfolio standards. We complement this work by examining to what extent these instruments can efficiently correct market failures caused by the emission externality, innovation spillovers, and capital market failures as well as providing guidance on how to use them appropriately. We argue that finance instruments are in general inferior to economic instruments in compensating for environmental externalities. However, these instruments seem suitable to effectively address knowledge spillovers and, in particular, capital market failures. Both aspects can be expected to be increasingly relevant as the world is trying to speed-up the structural change towards a low carbon economy as decided in the Paris Agreement under the United Nations Framework Convention on Climate Change.[6]

The remainder of this paper is structured as follows. The following Section 2 presents three major instruments for investment support (grants, interest subsidised loans, and guarantees). In Section 3, we characterise three main market failures relevant to clean energy investments and illustrate their effects from an investor's perspective. In Section 4, we examine whether finance instruments are suitable to address the respective market failure and provide policy recommendations. The final Section 5 concludes.

2. INSTRUMENTS FOR CLIMATE RELATED INVESTMENT SUPPORT

Subsidies to financing renewable energy or energy efficiency investments occur in a variety of instruments.[7] In this analysis, (i) simple grants, (ii) interest-subsidised loans, and (iii) loan guarantees are considered. While this set of instruments is not exhaustive, it still covers the majority of the subsidised financing volume and represents the main elements more complex instruments, such as structured funds, are composed of. Table 1 provides an overview of the major design parameters of a grant programme compared with concessional loans and loan guarantees. These design parameters largely determine the value of an instrument to the recipient (subsidy element) and the cost to the government.

6. According to the *Paris Agreement*, parties to the convention agree to "undertake rapid reductions [. . .], so as to achieve a balance between anthropogenic emissions by sources and removals by sinks of greenhouse gases in the second half of this century."

7. See Mclean et al. (2008) for an overview. A comprehensive comparison between the different instruments for government-intervention would be complex, since the different instruments imply different rights and obligations on the side of the investor (in our case sometimes the government). While the right of a debt-provider is merely restricted to receiving information and interest, the right of an equity provider may be different and involve decisions of the respective company. Similarly, the risks taken on by the institution providing the instrument are different according to the instrument. In our analysis, we concentrate on debt.

TABLE 1
Variables characterising the three major instruments for investment support which need to be determined when designing a corresponding support programme.

Grant	Concessional Loan	Guarantee
volume	volume	(implicit: loan characteristics.)
timing	timing	loan fraction covered
	interest (& risk free years)	risks covered
	seniority	trigger event
		pricing

2.1. Grants

A grant is typically a simple payment that is tied to a specific investment. As a support instrument used by a government or a public finance institution, the grant provision as such and its volume can be flexibly coupled to any politically justified parameters. In the field of clean energy, these parameters may be a list of technologies or activities that are eligible for support. It may also be a more abstract description of activities (e.g. by their goal or purpose) in order to keep the instrument flexible. In general, one may also link the grant provision to parameters such as emissions saved. This is, however, rarely the case, since it is often difficult to determine the emissions saved through an investment. If at all, expected savings for standardised technologies, which may be estimated up-front, are used.

The parameters may not be limited to climate related political goals. Typical examples of additional requirements are a certain maximum income of the supported household in order to focus the support on low-income households, or so-called local content rules that require part of the investment to be spent on technologies produced in the country that is funding the support scheme to support the regional economy. Grants are mainly used for two different purposes: (i) to fund early-stage clean technologies in their pre-maturity phase (research, development, and demonstration) and (ii) to subsidise the deployment of small-scale renewable energy.

In any case, the support scheme needs rules to determine whether support is granted, the volume of the support, as well as the timeframe. The latter has strong implications on dynamic incentives. A credible long-term commitment of a government to subsidise, e.g., certain energy efficiency improvements in residential buildings or renewable energy heating systems, might incentivise innovations in these technologies that could lead to cost reductions. A very limited subsidy scheme might not be able to trigger innovation activities.

2.2. Concessional Loans

Concessional loans use public money to extend loans for politically desired projects at more favourable conditions (maturity, interest, seniority) compared to commercial loans available on the market. If a concessional loan programme is used as a support policy, the conditions for the loan provision can—similar to the case of grants—be coupled to any parameters.

A number of reasons make the efficiency analysis for concessional loans fundamentally more complicated than the case for grants. One reason is that a concessional loan is characterised by more variables than a grant. While a grant is largely determined by volume and time of payment, a concessional loan needs to be further specified with respect to maturity, interest rate, including potential interest-free years at the beginning plus the seniority relative to other loans. A so-called senior loan will have to be paid back with priority while a "junior"-ranked loan might leave the priority to other loans, perhaps commercial lenders, who would find themselves in a more secure situation.

A second complexity relative to grants stems from the fact that the subsidy element of a concessional loan is not completely determined by the characteristics of the offered loan, but also by the risk profile of the recipient: At market prices, a high-risk borrower will normally be charged a higher interest rate than a low-risk borrower. Therefore, a concessional loan programme with a standardised interest rate will effectively mean a higher support for the high-risk- borrower than for the low-risk borrower.[8] This support-bias may give rise to standard adverse selection problems. Further, it is obvious that the absolute value of support increases with the volume to be financed.

An alternative to direct public lending are interest subsidies. In this case, the government does not directly provide loans, but rather offers a subsidy on the interest paid by the borrower. In such an interest softening mechanism, the borrower receives a loan at market conditions from a bank, but the interest repayment is partly taken over by the government such that the effective interest rate for the borrower is reduced.

2.3. Guarantees

Public guarantees to loans are typically used in order to lower the financing costs for a specific project. If a lender (e.g. a bank) receives a guarantee for some risks or part of a loan by a credible public institution, he is confronted with less risk and consequently may ask for a lower risk-premium on the interest rate, provide a higher loan amount or provide a loan at all.

A potential investment support programme structured as guarantees needs to specify the loan types (often loan purpose) that are eligible for a guarantee. Hence, implicitly most characteristics of the loan are part of the support scheme (maturity, seniority, volume, etc.). The added complexity of guarantees versus concessional loans comes from defining the trigger of the guarantee, the covered risks, and its pricing. While the pricing is often very similar to loan pricing (as a percentage of the covered loan volume), guarantees usually do not cover the full loan, but rather a certain fraction of the full amount—typically between 70–80% in practice (Honohan, 2010). One main reason is that coverage of (close to) 100% would induce moral hazard, as it would weaken the monitoring incentives of the lender (Anginer et al., 2014).[9] A major complexity—also when it comes to implementation—is the specification of risks to be taken by the public guarantor. In the event of default, it might be difficult to determine the drivers for this default ex-post. Depending on the risks covered by the guarantee, the value (or the subsidy embedded in the guarantee) may be higher for high-risk borrowers/projects.

8. This may be different if the interest rate is formulated relative to some interest rate that the borrower would have been offered on the market.

9. Green (2003) provides an analysis and examples on this moral hazard effect. One case is the Lithuanian *Rural Credit Guarantee Fund* that offered 100% coverage for loans for purchasing agricultural equipment and resulted in a huge amount of defaulted loans. When the Canadian Small Business Loans Act increased its guarantee coverage from 85% to 90%, lenders awarded loans to riskier clients resulting in a drastic increase in defaults.

3. MARKET FAILURES AND THE INVESTOR PERSPECTIVE

Two main market failures that are related to climate investments and frequently used to justify the promotion of climate investments are the negative externality caused by greenhouse gas emissions and the positive innovation externality (spillover).[10] One class of market imperfections, which is typically disregarded in analyses of instruments for environmental policy, are potential imperfections on capital markets. We argue, however, that it is essential to consider these market imperfections for at least two reasons. Firstly, climate related investments highly depend on services provided by capital markets, as renewable energy investments, e.g., are typically characterised by high up-front investment and low operating costs, which means that the cost structure is dominated by capital costs (Evans et al., 2009; Painuly, 2001; Wiser et al., 1997). For photovoltaics, the capital costs can account for more than 95% of total life cycle costs compared to a share of only 11% in the case of an oil power plant (Kannan et al., 2007). Secondly, climate policy increasingly acts through capital markets, as demonstrated above.

We therefore examine three major economic market failures related to low-carbon investments—(i) environmental emission externality, (ii) innovation spillovers and (iii) capital market failures (Stern and Rydge, 2012)—and, following Dinica (2006), translate these externalities into the investor perspective to illustrate their effects on the risk-return profile of climate investments.

3.1. Environmental Externalities & Innovation Spillovers

Emission externalities are characterised by a (negative) impact of one agent's emissions on the well-being of others. If this market failure is not corrected, e.g., through a price on emissions via taxes or a tradable permit scheme, then renewable energy or energy efficiency projects are commercially less attractive compared to otherwise similar projects based on conventional thermal power generation. There is a cost differential in favour of conventional technologies as long as the external costs of, e.g., fossil-based energy generation are not internalised.[11]

Innovation spillovers refer to the positive effect of inventions or innovations on other market actors. Technological change can be roughly divided into three stages: (i) invention: the creation of ideas, (ii) innovation: creation of new products or processes based on ideas, and (iii) deployment and diffusion: the actual penetration of the relevant market by the new technology (Popp, 2010). A firm invests in innovation activities if the expected returns of these activities exceed the costs. A successful technology innovation or deployment activity, however, usually leads to increased general knowledge due to its public goods nature. It is difficult to exclude others from these benefits. Even if intellectual property rights are in place, patents cannot entirely exclude other firms from profiting, as they can modify the patented innovation and utilise it (Levin et al., 1987). Hence, the social returns of innovation and

10. Other reasons frequently used to justify policy intervention include clean energy investments' contribution to energy security or strategic considerations of industrial policy aimed at establishing competitive advantages for local clean technology firms.

11. Renewable energy, however, might also be associated with negative externalities as negative impacts of visual and noise pollution from wind turbines on neighbouring properties' prices (Jensen et al., 2014) or changes in the landscape and impoverishment of natural diversity caused by hydropower (Kataria, 2009). Ladenburg and Lutzeyer (2012) provide a review on visual impacts of offshore wind.

deployment activities exceed the private returns of the innovator and result in an underprovision of such activities (Arrow, 1962; Griliches, 1992; Jaffe, 1987; Jones and Williams, 1998). Private actors invest too little, or possibly not at all, in certain socially beneficial innovation activities, as they cannot fully exploit the resulting benefits. Dechezlepretre et al. (2014) and Braun et al. (2010) provide evidence for knowledge spillovers in the clean-technology sector.

Environmental externalities and innovation spillovers may also interact. Successful innovation and diffusion of clean technologies reduce the marginal costs of achieving a desired pollution level. Policies targeting one of these externalities might also indirectly affect the other. Acemoglu et al. (2012) and Fischer (2008) show that it is inefficient if only one of both externalities is addressed by policy.[12] Hence, a portfolio of public policy instruments might be better suited to address both externalities (Bennear and Stavins, 2007; Jaffe et al., 2005).

3.2. Capital Market Failures

Less specific to renewable energy or energy efficiency, but relevant for the discussion of the government acting through the capital market, are imperfections on the capital market itself. This refers to cases where—despite a hypothetical absence of other market failures—the market does not allocate capital such that it is used most productively from a social point of view (see, e.g., Akerlof, 1970; Stiglitz and Weiss, 1981; and Stiglitz, 1993). In this context, we consider two types of capital market failures that systematically affect investment decisions on clean energy projects. These are (i) the lack of a liquid market for long-term debt (credit rationing) and (ii) imperfect credit markets.

These market failures are caused by information asymmetries between the lender (principal) and the potential borrower (agent) that knows the expected return and risk of his project. Expenditures to reduce this asymmetry might be sufficiently high such that transactions are limited or deterred. This credit rationing particularly affects long-term contracts, where information asymmetries and hence the risks for the lender are particularly large, and result in a lack of a market for *long-term debt* (Stiglitz, 1993).

However, even in successful transactions, *imperfections on credit markets* might result in interest rate rationing, i.e. a borrower receives a loan, but at unfavourable conditions (Jaffee and Stiglitz, 1990). We focus on two major externalities on capital markets that are particularly relevant for climate related projects. The first imperfection, *relationship banking*, refers to the relationship of the lender (bank) and the potential borrower. As the costs of screening a borrower, i.e. reducing information asymmetry, are sunk, a lender has an incentive for multiple transactions with the same borrower. A continuing relationship with a borrower results in cost savings, as the private information the bank obtained in previous transactions can be used for future deals. Hence, borrowers with a certain relationship with a bank are offered loans at more favourable conditions compared to unknown potential borrowers.[13]

Another imperfection is caused by *externalities of monitoring, selection, and lending* (Stiglitz, 1993). One main task of banks is the selection of projects and subsequent monitoring.

12. There are also interactions between externalities and capital market imperfections (see, e.g., Hoffmann et al., 2016). They may lead to optimal emission taxes deviating from a linear pigouvian tax.

13. A number of studies have shown empirical support for the positive effect of lending relationships on loan conditions (Bharath et al., 2011; Bräuning and Fecht, 2012; Jiménez and Saurina, 2004; Petersen and Rajan, 1995). Boot (2000) provides a survey on relationship banking.

Other lenders interpret a positive lending decision by a bank as a signal that the project was deemed as attractive after thorough screening, which informs part of their financing decision. Consequently, it will be easier for the project to raise additional financing. Furthermore, similar projects (e.g. using the same technology) will receive loans more easily or at better terms. Banks do not account for this positive externality on subsequent (other) lenders for the project or similar projects. Hence, there might be an under-provision of loans (or a provision of loans with bad conditions) for projects using novel technologies or project developers or technology firms with a limited track record.

These capital market failures are not exclusive for innovative clean technology, but are particularly present in this sector due to the following reason. Carpenter and Petersen (2002) show that particularly young high-tech firms have issues obtaining debt financing as high-tech investments are associated with higher uncertainty compared to conventional projects using established technologies. The fact that young firms do not have an established relationship with a lender further fosters credit rationing (Berger and Udell, 2002). The clean-technology sector plays an important role among small high-tech firms and attracts a large amount of venture capital investments.[14] Substantial information asymmetry between these firms and potential lenders aggravates the aforementioned capital market failures.

Capital market failures in this sector may be reinforced by the corresponding project finance characteristics. Due to the high up-front costs of renewable energy generation investments only utilities and large project developers are sufficiently capitalised to use on-balance sheet (corporate) finance (Kann, 2009). More typically, project finance structures are used.[15] These project finance structures are often long-term and characterised by a large share of debt, typically 70 to 80 % (Pollio, 1998), but do not involve any collateral as the lending is based on the project cash-flow. Collateral, however, is an important signalling device that can otherwise reduce the information asymmetry between lender and borrower.[16] Consequently, a limited capability to provide collateral can result in credit rationing (Bester, 1987).

The role of capital market failures for energy efficiency investments is similar, as they have a similar structure compared to renewable energy projects: high initial capital costs and lower energy costs in the future (Gillingham et al., 2009). Credit rationing for energy efficiency can be caused by limited information of the lender on the (certainty) of potential payoff of the energy efficiency investment and future energy prices (Golove and Eto, 1996; Gillingham and Palmer, 2014). Furthermore, energy efficiency loans are typically not secured as energy efficiency investments can typically not be used as collateral. However, capital market constraints seem to be less severe for energy efficiency compared to other clean technology investments. In developed countries, lenders can rely on credit ratings/histories of firms and households such that the lender does not have to rely on returns from energy savings for the repayment of a loan. An overview of recent empirical studies on industrial energy efficiency investments

14. In 2011, the US clean-tech sector attracted more than one quarter of the total venture investments (Pernick et al., 2014). This indicates the importance of small high-tech firms in the sector and might give an indication for credit rationing in the clean-tech sector as equity financing, e.g. through venture capital, seems to be an option chosen in the case of credit rationing (Carpenter and Petersen, 2002).

15. In a project finance structure, the project is developed and financed off-balance sheet. This means that financing is based upon the future cash flows of the project and only secured by the project assets (rather than the general assets of the sponsor). In 2014, project finance accounted for almost 32% of worldwide investments in utility-scale renewable energy (McCrone et al., 2015).

16. Collateral can be used by the lender to induce a self-selection among borrowers. A high-risk borrower, knowing that his project has a high probability to default, is less likely to accept collateral requirements set by the lender. In contrast, low-risk investors will reveal themselves by accepting the collateral requirement (Bester, 1987).

by Trianni et al. (2016) shows that, in developing countries, alternative options for investing scarce capital play a more important role in deterring energy efficiency investments than a limited access to capital. Hence, credit constraints are more relevant in developing countries and for borrowers with a poor credit rating (Palmer et al., 2012).[17] Although varying in magnitude, capital market failures therefore affect all types of clean energy related investments.

3.3. The Investor Perspective

When discussing market failures and policy measures in clean energy, it is helpful to complement the policy-maker perspective by an investor perspective through translating the market failures relating to clean energy investments into consequences for the risk-return profile of these projects.[18] A potential investor decides on a certain investment opportunity based on the risk-return characteristics of the underlying project. Hence, an investor's decision on whether or not to move forward with a certain project is indirectly affected by market failures through their effect on the (perceived) risk-return of the underlying project. Furthermore, instruments of public investment support directly influence this risk-return profile. Those instruments may provide financing below market interest rates (concessional loans) or take risk (guarantees), which can directly increase an investment's attractiveness by counteracting the symptoms of market failures.

Environmental externalities affect the risk-profitability of a climate investment, but rather indirectly: If the negative environmental externalities are not internalised, alternatives to clean energy projects—e.g. fossil fuel based electricity or less energy efficient production technology in case of industrial energy efficiency—have higher returns than they should have from a social perspective. Hence, the relative risk-return profile of an emission mitigation project is negatively affected. Knowledge spillovers affect the risk-return characteristics of the clean energy project itself. As not all benefits are exclusive to the investor, the private return is below the social return of an innovative investment. Furthermore, innovative activities, e.g. the deployment of a new technology, have higher risks compared to using established dirty technologies. Finally, capital market imperfections have a direct impact on the financial characteristics of a project. As argued above, capital market imperfections result in worse loan conditions—e.g. higher interest rates—and hence negatively affect the profitability of a project. Hence, all these market imperfections—if uncorrected—decrease the attractiveness of a clean energy investment relative to other investments.

4. ECONOMIC ANALYSIS OF FINANCE INSTRUMENTS

After characterising main market failures associated with clean energy investments and their effects from the investors' perspective above, we now turn to examining the ability of finance instruments to compensate those market failures. For this evaluation, it is important to consider how much value is transferred through such investment support, i.e., the subsidy element

17. Apeaning and Thollander (2013) and Kostka et al. (2013) provide empirical evidence for the relevance of credit constraints for energy efficiency investments. However, overall, other market failures as imperfect information, principal-agent issues, differences between private and social discount rates, or bounded rationality seem to be at least as important in deterring energy efficiency investments (for a review, see Gillingham and Palmer, 2014; and Linares and Labandeira, 2009).

18. Wiser et al. (1997) provided an early contribution focussing on barriers for renewable energy financing from an investor perspective. Dinica (2006) analyses the risk characteristics of support instruments might affect investor behaviour and hence the deployment of renewable energy technologies.

of such an instrument, as characterised in Section 2. In this section, we first examine to what extent finance instruments are capable of correcting each of these market failures (in comparison to alternative policies) and the information requirements to design those instruments cost-efficiently. Finally, we provide some brief policy recommendations on designing and applying public finance instruments, particularly in cases where alternative first-best policies are unavailable. Table 2 summarises the results of the analysis and the policy recommendations.

4.1. Environmental Externalities & Innovation Spillovers

Both for environmental externalities and innovation spillovers, instruments of investment support do not directly correct the respective market failure, as, e.g., an emission trading scheme or emission tax do in case of the environmental externality, but rather address their symptoms, namely their negative impact on the risk-return profile of a clean energy investment. Thereby, the incentive to realise the project would be increased, compensating its disadvantage relative to other projects emitting CO_2 or profiting from knowledge spillovers (see Table 2). In order to achieve the internalisation of both externalities through investment support efficiently, the value / cost of the respective finance instrument must not exceed the social value of the avoided emission externality and the knowledge spillover.

Determining the value of the environmental externality requires the amount of avoided emissions and a (hypothetical) price per unit of emissions. In the absence of a CO_2 price, assumptions on a price are required, potentially based on other areas/sectors where CO_2 prices exist.[19] Overall, market-based instruments are more suitable to correct the emission externality at least cost due to two main advantages. Firstly, these instruments provide incentives through markets signals that encourage emission abatement where it can be achieved at least cost (Stavins, 2003). Hence, these instruments do not require detailed information of firms' or technologies' marginal abatement costs. In order to apply financial instruments efficiently, the policy maker would require this information in order to target financial support at the most cost-efficient investments. Secondly, revenues from market-based instruments—revenues from emission taxes or from auctioned permits in emission trading schemes—might be used to reduce other distortionary taxes resulting in the beneficial "revenue-recycling effect" (Goulder and Parry, 2008; Goulder et al., 1997) or to support climate investments in developing economies, where a carbon price might not be feasible (Bowen et al., 2014).

Overall, finance instruments seem to be suitable for targeting this market failure. Evidence suggests that, even in the presence of economic instruments that provide incentives for innovation and deployment of clean technologies, the market failures associated with knowledge spillover cannot be compensated entirely (Jaffe et al., 2005; Popp et al., 2010). Johnstone et al. (2010) find that direct investment incentives, e.g. grants, concessional loans, and guarantees, effectively support innovation in clean technology, particularly in the case of less mature technologies. Olmos et al. (2012) provide a comprehensive analysis on the suitability of different finance instruments for supporting innovation and deployment of clean technologies based on features of innovation that vary across clean technologies, e.g. the maturity of the respective technology. Public (concessional) loans and loan guarantees seem particularly suitable for close-to-maturity technologies that are expected to be profitable large-scale deploy-

19. Note that in general one might argue that the socially optimal CO_2 price should be based on some global cost benefit considerations. We abstract from the issue of a globally optimal emission level but rather look at the question of cost-efficient abatement.

TABLE 2

Summary of market imperfections, their effect on the investor perspective, and the analysis of investment support instruments.

Market Imperfection	Economic Mechanism	Mapping to Investor's Perspective	Ability of Investment Support Instruments to Compensate	Policy Considerations
Emission Externality	A missing emission price leads to socially inefficient high return for conventional / non-clean investments.	Relative return below social optimum (as compared to conventional alternative).	Finance instruments for clean energy projects reduce financing costs and hence increase their relative return. If the subsidy element is appropriately sized, negative effects of externality on risk-return profile can be compensated.	Market-based instruments are superior policy. If not available, investment support can be considered. To avoid inefficiency, subsidy element of finance instrument should not exceed the (estimated) value of avoided externality.
Innovation Spillover	Innovative projects bear higher risk and provide social benefits through knowledge spillovers that are not reflected in the return.	Increased risk not adequately rewarded and return below social optimum.	Investment support instruments can reduce financing costs and hence (i) mitigate the risk-premium that has to be paid to private lenders and (ii) increase the return to decrease / mitigate the gap between private and social return.	Investment support instruments are suitable to compensate for spillovers. Grants should be applied to early-stage innovation, while subsidised loans and guarantees are best suited to support the deployment of (close to maturity) clean innovations.
Capital Market Failure	Due to information asymmetries between investor and lender, financing is inefficiently expensive (or not available at all).	Return below social optimum (or equal to zero in case of the project not being implemented).	Instruments of investment support directly target the capital market failure. By improving financing costs (through grants, interest subsidies, or guarantees) or direct concessional lending, investment returns can be increased.	Policy interventions through finance instruments are optimal. Interest rate subsidies and guarantees are preferred to investment grants due to lower costs. Direct subsidised lending should be used if (i) government (or public bank) has a better ability to screen and monitor or (ii) a market for (long-term) debt is absent.

ments in the future. By providing a concessional loan or a loan guarantee that improves the loan conditions, the government subsidises the investor conducting the innovative project by compensating for the knowledge spillovers other actors benefit from. This subsidy lowers the financing costs and hence increases the private return (and lowers the risk) and reduces / closes the gap between the private and the social return of innovative activities with knowledge spillovers. Grants can, in principle, be used for any clean innovation activity. Considering the higher costs of this instrument—in contrast to loans, grants are not paid back—it seems particularly suitable to support early-stage clean technology innovation which is commercially the least attractive. For concessional loans or guarantees, the value of the support is determined relative to the same instrument at market prices. Note, however, that this does not solve the issue of determining the appropriate level of support (which exists for clean energy technologies as well as for all other innovations) that should not supersede the benefits, i.e. the social value of knowledge spillovers that is challenging to quantify (Hall, 1996).[20]

4.2. Capital Market Failures

Providing public finance instruments means that the government acts as player on the capital market. In contrast to compensating emission externalities or knowledge spillovers, here the public intervention is aimed at the market where the failure actually occurs. According to previous studies, public intervention on financial markets can effectively correct market imperfections (see, e.g., Arping et al., 2010; Gale, 1990; Honohan, 2010; Janda, 2011; Philippon and Skreta, 2012).

Policy interventions on capital markets have the ability to remedy the negative effects of market failures on climate related investments. The provision of (concessional) public loans is the most direct instrument: the regulator provides debt for climate related investments that is underprovided, or offered at unfavourable conditions, by private lenders due to asymmetric information. This instrument seems particularly suitable for the case of the lack of a market for long-term debt for climate related investments (credit rationing). As a loan guarantee partly takes over the risk of default, the lender can improve the loan conditions, e.g. reduce the interest rate, of loans for clean energy investments. In the absence of a guarantee, the private lender charges a higher interest to account for the risk, while the interest payments of the borrower can be reduced through interest subsidies.

In spite of the differences of both instruments, interest rate subsidies and loan guarantees generally have the same effect: they diminish the unfavourable loan conditions induced by information asymmetries. Minelli and Modica (2009) show that both subsidised loans and loan guarantees are optimal to correct market failures on credit markets and imply similar costs to the regulator.[21] As guarantees are only paid in the case of failure, the costs of this instrument increase with the guaranteed loan's risk of default and maturity (Honohan, 2010). The costs of interest subsidies (also the subsidy component) occur even in the case of a successful project and rise with difference to the market interest, volume, and maturity. Hence, for both instruments the costs increase with the magnitude of market failure. Grants also have the ability to remedy capital market failures, but, as they are normally not paid back, grants are in general the more expensive instrument and hence inferior to loans and guarantees in

20. See Kaiser (2002) and Nelson (2009) for an overview of alternative approaches of approximating knowledge spillovers.

21. Janda (2011) argues that the costs of guarantees and interest subsidies depend on the diversity of projects, i.e. the difference in the success probability of high-risk and low-risk projects. The author shows that guarantees are less costly in case of high project diversity, while interest subsidies are less costly in case of low project diversity.

addressing capital market failures (Minelli and Modica, 2009). With respect to costs, direct concessional lending by the state combines the attributes of interest subsidies and guarantees. If government budget is used to subsidise interest, the costs are similar to paying an interest subsidy on a loan provided by a private lender. The amount of the subsidy, however, is likely to be smaller in case of public loans, as government institutions—at least in developed countries –usually have lower refinancing costs than private institutions. In case of a default, the government has costs amounting to the defaulted loan, which is similar to the cost attributes of guarantees. The latter, however, are potentially lower as they typically do not cover the whole loan amount.

In addition to the static effects, capital market interventions also have a dynamic effect by reducing information asymmetries over time. When projects supported by public finance instruments materialise, private lenders acquire information on those projects. Hence, lenders have better information on the profitability of investments in, e.g. certain clean technologies. The same applies to clean technology firms or project developers that might build up a track record that can reduce the information asymmetry between them and lenders. Overall, finance instruments seem to be the instruments of choice to correct capital market failures related to clean energy investments.

4.3. Policy Considerations

Climate related investments, as renewable energy and energy efficiency projects in the real world, are subject to more than one market imperfection and frequently a number of policy instruments and incentives coexist. Designing appropriate support policy schemes in such a context is challenging (Fischer and Preonas, 2010; Sijm, 2005; Sorrell and Sijm, 2003). Nevertheless, their design will benefit from a clear understanding of the individual market imperfections. Note that in order to implement the first-best optimum, theoretically each externality needs to be internalised and this could be achieved with one instrument per externality. If we assume, however, that this design of multiple internalisation policies is not possible, then one approach could be the following: In general, and if all the externalities could be quantified, one would be able to aggregate them with respect to their effect on risk and return. These aggregate effects could then be compensated through support policies.

As market-based instruments are the first-best choice to internalise the emission externality, other policies, such as finance instruments, should only be considered if an emission price is (politically) not feasible. When using finance instruments to correct the emission externality, government support should aim to achieve a certain benefit at least cost, which requires some estimate of the benefit of saved emissions. In the case of a renewable energy project, e.g., expected emission savings can be estimated based on assumptions about: the technology, the capacity, the expected lifetime, and some reference generation technology. In the case of an energy efficiency investment, emission savings estimations have to be based on the lifetime and usage of the technology. Quantifying the value of the externality requires an emission (shadow) price assumption to value the avoided emissions. A potential approach for such a quantification of emissions avoided by renewable energy projects could be the use of standardised baselines as suggested by Spalding-Fecher and Michaelowa (2013) for the Clean Development Mechanism. A corresponding estimation for an energy efficiency project (e.g. a new technology) might be less straightforward.[22] The costs of the applied finance instrument,

22. With some assumptions, it might be possible to estimate the expected emissions saved, but the business-as-usual reference is less obvious if the investment in a new cleaner technology was due to other reasons than just increased energy efficiency.

i.e. the subsidy element, should not exceed the benefit of the avoided emission externality. Even under these considerations, investment support for clean energy might induce additional inefficiencies. Consider subsidies to an energy efficiency investment that illustrates the non-equivalence of an emission price on the one hand and subsidising carbon free technology on the other. Inefficiencies particularly result if the (subsidised) investment also raises the emission baseline. An example would be the provision of low-interest loans for cars with relatively low emissions. On top of making relatively efficient cars more attractive, the low-interest loan may have two additional effects: (i) it subsidises the use of cars in general (leading to additional emissions, especially if clean / cleaner means of transportation are substituted) and (ii) the subsidy element increases with the price of the vehicle, which typically means a higher subsidy to bigger (more expensive) cars often emitting more carbon than smaller (cheaper) ones.

In contrast to the emission externality, finance instruments are suitable to address market failures due to knowledge spillovers and, in particular, market failures on capital markets. In case of knowledge spillovers, a main guideline for using financial support is that grants should be used for early-stage, far-from-maturity clean-tech innovation investments, whereas the support of more mature technologies, in particular their deployment, can be more cost efficiently supported by subsidised loans or even guarantees. In order to avoid crowding out, particularly loans and guarantees should be only employed for innovation and deployment projects, where (i) the investors have difficulties receiving private finance due to the gap between social and private returns or (ii) the public sector is more knowledgeable / experienced with the respective technology than the private sector (Olmos et al., 2012).

Within the group of finance instruments, loan guarantees and interest subsidies are the most appropriate policies to address capital market failures as they are generally more cost efficient compared to (investment) grants. However, direct government lending bears the risk of crowding out private lending. Whether direct (concessional) lending is an appropriate instrument also depends on the development of the financial sector and its liquidity.[23] In case of limited liquidity, direct public lending might be the only instrument to provide finance to clean energy projects. This could be the case in emerging and developing countries as well as in developed countries in periods of credit crunches during, e.g., a financial crisis.[24] Furthermore, when the financial sector development is low, the public sector lender might have an advantage in assessing projects of potential borrowers (lower information asymmetry) due to better screening skills based on previous experience and knowledge. Hence, concessional lending by, e.g. bilateral or multilateral development banks, are particularly suitable to finance clean energy investments in emerging and developing countries, where financial sectors are less developed.[25] In this case, direct public lending might be an effective tool to reduce the information asymmetry by providing finance to pilot projects. The learning effect for private lenders might be increased by public and private co-financing of clean energy projects.

23. Lending by governments or mandated public finance institutions in fact may either happen directly or through other commercial banks which are for these projects refinanced by public finance institutions (so-called on-lending). Inter alia this is used to limit crowding out or to use specific strengths of the commercial bank such as an established client base.

24. Due to the current expansionary monetary policy in a majority of OECD countries and the resulting low interest rates, liquidity seems, at least currently, not to be a major issue on credit markets in developed economies.

25. Brunnschweiler (2010) provides empirical evidence for the importance of financial sector development for the deployment of renewable energy in emerging and developing countries.

5. CONCLUSIONS

In this paper, we raise the issue of whether the intensified use of public finance instruments to support climate related investments is compatible with facilitating the structural change at least cost to society, or whether they run the risk of being overly expensive or extensively using scarce public funds, therefore impeding the transition towards a low carbon economy.

In general, finance instruments are capable of compensating for the main market imperfections associated with clean energy investments. From an investor's perspective, all market failures analysed here negatively affect the risk-return characteristics of the underlying clean energy investment. As public finance instruments for investment support are able to directly influence risk and capital cost (i.e. return), they can be flexibly designed to compensate where climate related investments are less attractive from the investors' perspective than they should be—based on societal / economic considerations. Whether these instruments are the first-best choice, however, largely differs across market failures and investment environments.

With respect to emission externalities, policies of finance support are economically inferior to market-based instruments. Whenever economic instruments are not politically possible, e.g. in emerging and developing countries, finance instruments might be second-best choice. When applying these instruments, however, the design of public investment support programmes—e.g. the magnitude of an interest subsidy or the proportion of a loan that is covered by a guarantee—should be based on cost benefit considerations. The cost of a finance instrument and the subsidy element should not exceed the value of abated emissions.

An additional advantage of market-based instruments, if designed appropriately, is their ability to provide incentives to innovate and deploy clean technologies (Bennear and Stavins, 2007; Jaffe et al., 2005). Although these policies cannot fully compensate for the market failures related to innovation and deployment, they can reduce the social cost of innovation policies, as, with a carbon price in place, clean technology innovation investments require less financial support. As economic instruments cannot fully overcome the innovation market failures, a combination of this policy with financial support innovation and deployment can compensate both market failures at least cost. Finally, finance instruments are optimal policies to address capital market failures.

Given the global consensus of limiting global warming, a substantial structural change in the energy infrastructure is required. Based on our examination, this speaks strongly in favour of (i) introducing carbon-price-based regulation to cope with the corresponding externality and (ii) focusing on understanding the non-emission market imperfections when designing investment support policies in order to avoid inefficient government spending. While it can be technically challenging to quantify all market imperfections, understanding them provides a reliable foundation when designing policy to moderate structural change.

ACKNOWLEDGMENTS

We thank Christine Grüning, Andreas Löschel, and two anonymous referees for their valuable input and are grateful for comments from the participants of the 12th European Energy Conference of the International Association for Energy Economics, where an early version of this article was presented. We gratefully acknowledge funding from the German Federal Ministry for the Environment, Nature Conservation, Building and Nuclear Safety (BMUB). Opinions and remaining errors are our own.

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Chapter 3

Directed Technical Change and Energy Intensity Dynamics: Structural Change vs. Energy Efficiency

Reference for this Paper:

Haas, Christian and Karol Kempa (2018), "Directed Technical Change and Energy Intensity Dynamics: Structural Change vs. Energy Efficiency", *Energy Journal* 39(4), 127-151. DOI: 10.5547/01956574.39.4.chaa.

Conferences with Review Process:

Annual Conference of the Verein für Socialpolitk, Augsburg, 2016.

Annual Conference of the European Association of Environmental and Resource Economists, Athens, 2017 (presentation by Christian Haas).

15th European Conference of the International Associations for Energy Economics, Vienna, 2017.

Workshops:

MAGKS Doctoral Colloquium, Marburg, March 2015.

Directed Technical Change and Energy Intensity Dynamics: Structural Change vs. Energy Efficiency

Christian Haas and Karol Kempa***

ABSTRACT

This paper uses a model with Directed Technical Change to theoretically analyse observable heterogeneous energy intensity developments. Based on the empirical evidence, we decompose changes in aggregate energy intensity into structural changes in the economy (*structural effect*) and within-sector energy efficiency improvements (*efficiency effect*). The relative importance of these effects is determined by energy price growth and sectoral productivities that drive the direction of technical change. When research is directed to the labour-intensive sector, the *structural effect* is the main driver of energy intensity dynamics. In contrast, the *efficiency effect* dominates energy intensity developments, when research is directed to energy-intensive industries. Increasing energy price generally leads to lower energy intensities and temporal energy price shocks might induce a permanent redirection of innovation activities. We calibrate the model to empirical data and simulate energy intensity developments across countries. The results of our very stylised model are largely consistent with empirical evidence.

Keywords: Directed technical change, Energy efficiency, Energy intensity, Structural change

https://doi.org/10.5547/01956574.39.4.chaa

1. INTRODUCTION

The relationship of energy use and economic activity has been a recurring theme in the political and academic debate, particularly since the energy crisis in the 1970s. Main reasons include the high dependency on fossil fuel energy carriers in energy generation—80.6% in 2014 (IEA, 2015)—and the resulting consequences for the world climate as well as increasing energy prices. A promising way to lower emission levels and meet climate policy targets is reducing energy intensity, i.e. decreasing the input of energy for production of a given output.

Since the energy crisis in the 1970s, numerous studies have analysed the development of energy intensities.[1] Studies covering the period before the energy crisis, i.e. 1950–1970, show increasing or constant energy intensities across most of the analysed developed and emerging economies (Casler and Hannon, 1989; Hannesson, 2002; Proops, 1984). For the period after the energy

1. A theme related to the energy intensity literature is the so-called rebound effect, which can be decomposed into a direct rebound, an indirect rebound, and an economy wide (or growth) effect (Binswanger, 2001;00 Brookes, 2004; Greening et al., 2000; Khazzoom, 1980; Khazzoom, 1987; Qiu, 2014; Schipper and Grubb, 2000).

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crisis, however, there is strong evidence for substantial reductions in energy intensity in the majority of developed economies (Csereklyei et al., 2016; Greening et al., 1998; Grossi and Mussini, 2017; Liddle, 2012; Mulder and de Groot, 2012; Sun, 1998; Voigt et al., 2014; Wang, 2013).[2] In addition to analysing trends of overall energy intensities across countries, numerous studies use, e.g., index- or structural decomposition analyses to disaggregate energy intensity into its driving forces (Ang, 2004; Loschel et al., 2015; Mendiluce et al., 2010; Mulder, 2015; Sue Wing, 2008).[3] Most studies decompose energy intensity into an *efficiency effect*[4] and a *structural effect*. The former describes energy efficiency improvements within sectors, i.e. reductions in sectoral energy intensities due to e.g. substitution of energy by other factors or energy-saving technological progress. The *structural effect* refers to structural adjustments towards sectors with low energy intensities.

Mulder and de Groot (2012) decompose the development of energy intensities across 50 sectors in 18 OECD countries for the period 1970–2005. The authors find an important contribution of the structural effect for energy intensity reductions (25% in all analysed OECD economies). However, the relative importance of the efficiency effect seems to be stronger.[5] A recent and very comprehensive decomposition analysis was conducted by Voigt et al. (2014). Using the World Input-Output Database (WIOD) covering 34 sectors in 40 countries from 1995–2007, Voigt et al., (2014) show a conspicuous divergence in the importance of the structural and the efficiency effect for energy intensity developments across countries. In around one third of all developed economies energy intensity reductions are primarily caused by a restructuring of the economy towards sectors with low energy intensities (structural effect). In the reminder of all industrial countries, the efficiency effect is primarily responsible for the decline in energy intensity. Overall, the data analyses on energy intensities show the following trends:

1. while energy intensities were constant or increasing in the majority of economies until the early 1970s, they systematically decreased since the energy crisis;
2. the contributions of energy intensity reductions within industries, e.g. through technological progress (efficiency effect) and structural change towards less energy-intensive economic activities (structural effect) to energy intensity reduction differ substantially across countries.

In contrast to the extensive empirical literature on energy intensity developments, there is a lack of theoretical approaches to analyse the underlying mechanisms of the trends described above. Recent studies, as Mulder and de Groot (2012) and Voigt et al. (2014), highlight the exploration of the determinants of these developments, including the role of technological change, as directions of future research. Our paper aims to fill this research gap by providing a, to our knowledge, first the-

2. Greening et al. (1998) analyse ten developed economies from 1971–1991 and find energy intensity reductions between 37.5% (Norway) and 61.7% (Japan). For a similar period (1973–1990), Sun (1998) finds a reduction of energy intensity of 26.2% across OECD countries. Liddle (2012) and Wang (2013) find similar results using more recent data. In spite of continuous reductions in energy intensities, there is still a high potential for energy efficiency improvements (Velthuijsen, 1993; Worrell et al., 2009).

3. Ang and Zhang (2000) found 124 studies applied decomposition analyses related to energy-based emissions and energy demand. Only ten years later, the number of studies almost doubled (Su and Ang, 2012).

4. The efficiency effect is also referred to as technology or (sectoral) intensity effect.

5. Sun (1998) finds a contribution of the efficiency effect of 75.5% from 1973–1980 that even increased to 90% from 1980–1985 and 92.8% from 1985–1990. Greening et al. (1998) also find that energy efficiency improvements within sectors are the main drivers of energy intensity decline.

oretical analysis of energy intensity dynamics.[6] We analyse how endogenous technical change and energy price affect the direction and magnitude of the structural and the efficiency effect.

For this purpose, we use a theoretical Directed Technical Change (DTC) framework as proposed by Acemoglu (1998, 2002) to analyse the observed trends in energy intensity dynamics. The application of DTC model frameworks to examine the relation of technical change and the use of energy or natural resources is not new. Di Maria and van der Werf (2008b) use a two-sector DTC model with an energy- and a labour-intensive sector to analyse the effect of unilateral climate policy on carbon leakage, while Di Maria and Smulders (2004) examine the pollution haven effect. Di Maria and Valente (2008) and Pittel and Bretschger (2010) study whether technical change is resource-augmenting within DTC model frameworks. André and Smulders (2014) investigate long-run trends in oil dependency by introducing energy input from non-renewable resources into a DTC model setup.

Our analysis mainly builds on the DTC model of Acemoglu et al. (2012). We use a marginally modified version of their model with exhaustible resources, as it ideally serves the purpose of our analysis. Since we want to analyse the effect of energy prices on innovation and energy use, we need a model framework with energy as input factor and endogenous technical change. Furthermore, we require a multi-sectoral setup to explicitly differentiate between structural adjustments between sectors and within-sector energy efficiency improvements. Based on the model, we provide new insights on the effects of energy price growth and endogenous technical change on energy intensity developments. We show how energy price growth and the relative productivity of the labour- and the energy-intensive sector affect the direction of technical change. After decomposing overall energy intensity into efficiency effect and structural effect, we show how the direction and magnitude of both effects is affected by technical change and energy price growth. We find that the efficiency effect dominates the evolution of energy intensity in economies, when research is directed to the energy-intensive sector. When research is directed to the labour-intensive sector, the structural effect is the main driver of energy intensity dynamics. By calibrating the model to empirical data for 26 OECD countries, we illustrate how energy intensity development, driven by these two effects, varies across these countries.

The remainder of the paper is structured as follows. In Section 2 we present the model and characterise the equilibrium. Section 3 contains the main analysis. We decompose energy intensity into structural and efficiency effect and show how both effects are affected by technical change and energy price growth. Section 4 provides simulations to illustrate the model results. In Section 5, we discuss our results and possible extensions of the model. Section 6 concludes. Proofs of several main results are available in the technical Online Appendix.

2 THE MODEL

In this section, we introduce the model framework, which is based on the setup of Acemoglu et al. (2012) and modified in the following ways. The authors model the energy price as function of the resource stock, since they analyse how the depletion of an exhaustible resource might induce a redirection of technical change towards a clean sector due to a continuously increasing price. In contrast, we model an exogenous price for energy and endogenous energy use, as our focus is the analysis of heterogeneous energy intensity dynamics across countries with different energy price

6. A recent exception is Cao (2017), who uses a different model framework. A main difference is that the author explicitly models the production of energy. In contrast to Cao (2017), the direction of technical change is determined endogenously in our analysis.

growth rates. Furthermore, we formulate our model in continuous time. This redefinition of the time dimension allows an extension of the model by an analytical decomposition of energy intensity into a structural and an efficiency effect, which we present in Section 3.

2.1 Model Framework

Consider an economy with infinitely-lived households consisting of scientists, entrepreneurs, and workers. Consumer behaviour can be described by a representative household that maximises its utility (U) through consumption ($C(t)$) of the only final product at time t with the utility function

$$U \equiv \int_0^\infty e^{-\rho t} u\left(C(t)\right) dt, \tag{1}$$

where ρ is the rate of time preference. The unique final good ($Y(t)$) is assembled from sectoral outputs of a labour-intensive sector ($Y_l(t)$) and an energy-intensive sector ($Y_e(t)$) according to

$$Y(t) = \left(Y_l(t)^{\frac{\varepsilon-1}{\varepsilon}} + Y_e(t)^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}. \tag{2}$$

Markets for $Y(t)$, $Y_l(t)$, and $Y_e(t)$ are perfectly competitive. The outputs of the labour-intensive and the energy-intensive sector are imperfect substitutes, where ε (with $\varepsilon > 0$) is the elasticity of substitution between both goods. In the following, the two goods will be referred to as (gross) substitutes when $\varepsilon > 1$ and (gross) complements in the case of $\varepsilon < 1$. $\varepsilon = 1$ is not considered, as in this case the production function converges to the Cobb-Douglas type and hence technical change is neutral to the input factors.

In each sector $j \in \{l, e\}$, labour ($L_j(t)$) and a sector specific set of machines are used for production. Each machine type i in sector j, $x_{ji}(t)$, has an individual productivity $A_{ji}(t)$. The production in the energy-intensive sector additionally requires energy $E(t)$. The production functions of both sectors are:

$$Y_l(t) = L_l(t)^{1-\alpha} \int_0^1 A_{li}(t)^{1-\alpha} x_{li}(t)^{\alpha} di, \tag{3}$$

$$Y_e(t) = E(t)^{\alpha_2} L_e(t)^{1-\alpha} \int_0^1 A_{ei}(t)^{1-\alpha_1} x_{ei}(t)^{\alpha_1} di, \tag{4}$$

with $\alpha = \alpha_1 + \alpha_2$ and $\alpha, \alpha_1, \alpha_2 \in (0,1)$. The aggregate productivity of sector $j \in \{l, e\}$ is defined as

$$A_j(t) \equiv \int_0^1 A_{ji}(t) di. \tag{5}$$

This definition will be used for the subsequent analysis of the direction of research. Labour is assumed to be supplied inelastically. Normalising labour supply to 1, the labour market clearing condition is

$$L_l(t) + L_e(t) \leq 1. \tag{6}$$

Energy is supplied at per unit costs of $c_E(t)$. With respect to the evolution of energy costs over time, we consider different scenarios that are discussed in Section 3.

Machines are produced with an identical, linear production technology at identical costs of ψ units of the final product and supplied under monopolistic competition. Market clearing for the unique final good implies

$$Y(t) = C(t) + \psi\left(\int_0^1 x_{li}(t)di + \int_0^1 x_{ei}(t)di\right) + c_E(t)E(t). \tag{7}$$

Technological progress is driven by quality improvements of machines. Each machine is owned by an entrepreneur, the measure of entrepreneurs in each sector is normalised to one, respectively. At the same time, scientists (entrants) attempt to enter the market (become an entrepreneur) through innovation. Scientist direct their research at either the labour- or energy-intensive sector. With the probability $\eta_j \in (0,1)$, the innovation attempt is a success and the scientists is randomly allocated to a specific machine, increases its quality by $\gamma > 0$, receives a patent, and becomes the sole producer of this machine variety. The entrepreneur that used the old version of this machine leaves the market and joins the pool of scientists. Normalising the mass of scientists to one, the market clearing condition for scientists is

$$s_l(t) + s_e(t) \leq 1, \tag{8}$$

with $s_j(t)$ denoting the mass of scientists directing their research towards sector j. Due to this innovation process, together with (5), the aggregate sector productivity, $A_j(t)$, improves over time according to the following law of motion:

$$\dot{A}_j(t) = s_j(t)\eta_j\gamma A_j(t). \tag{9}$$

2.2 Research Incentives and Directed Technical Change

In this subsection, we define the equilibrium, which is formally derived in the Online Appendix A, and analyse the direction of research.

> **Definition 1** *An equilibrium is given by prices for sector outputs ($p_j(t)$), machines ($p_{ij}(t)$) and labour ($w_j(t)$), demands for machines ($x_{ji}(t)$), the exogenous energy price ($c_E(t)$), sector outputs ($Y_j(t)$), labour ($L_j(t)$) and energy ($E(t)$) inputs in sector $j = \{e,l\}$, such that at t: $p_{ij}(t), x_{ij}(t)$ maximizes profits of producers of machine* **i** *in sector j; $L_e(t), E(t)$ maximizes profits of producers in the energy intensive sector, $L_l(t)$ maximizes profits of producers in the labour intensive sector; $Y_j(t)$ maximizes profits of final good producer; $s_j(t)$ maximizes expected profits of researchers in sector j.*

In order to determine technical change, i.e. the development of productivities in the energy-intensive and the labour-intensive sector, the direction of research has to be examined. The research incentives of scientists are determined by the profitability of research in both sectors, i.e. the expected firm value due to the patented innovation in the respective sector. Following Acemoglu et al. (2012) and Daubanes et al. (2013), a patent for an improved sector specific machine is enforced for the smallest definable unit of time. This assumption simplifies the expected firm value to the profit in t.[7] Combining (A.13), (A.15), and (A.16) with (B.1) yields the relative profitability of research as:

$$\frac{\Pi_l(t)}{\Pi_e(t)} = \kappa \frac{\eta_l c_E(t)^{\alpha_2(\varepsilon-1)}}{\eta_e} \frac{A_l(t)^{-\varphi}}{A_e(t)^{-\varphi_1}} \tag{10}$$

7. A detailed analysis of the direction of technical change with longer (infinite) duration, where the scientist derives monopoly profits until another scientist improves her machine variety and hence replaces her, can be found in Online Appendix D. Although this approach is more general, this simplification does not affect our further analysis.

with $\kappa \equiv \frac{(1-\alpha)\alpha}{(1-\alpha_1)}\left(\frac{\alpha^{2\alpha}}{\psi^{\alpha_2}\alpha_2^{\alpha_2}}\right)^{\varepsilon-1}\alpha_1^{2\alpha_1(1-\varepsilon)-1}$, $\varphi \equiv (1-\alpha)(1-\varepsilon)$, $\varphi_1 \equiv (1-\alpha_1)(1-\varepsilon)$. Relative profitability is a function of time-invariant parameters, the energy price, research efforts in both sectors as well as productivities. The following lemma can be derived from expression (10).

Lemma 1 *In equilibrium, research is directed to the energy-intensive sector only, when* $A_e(t)^{(-\varphi_1)}\eta_e > \kappa\eta_l c_E(t)^{\alpha_2(\varepsilon-1)} A_l(t)^{(-\varphi)}$*, to the labour-intensive sector only, when* $A_e(t)^{(-\varphi_1)}\eta_e < \kappa\eta_l c_E(t)^{\alpha_2(\varepsilon-1)} A_l(t)^{(-\varphi)}$*, and to both sectors, when* $A_h(t)^{(-\varphi_1)}\eta_e = \kappa\eta_l c_E(t)^{\alpha_2(\varepsilon-1)} A_l(t)^{(-\varphi)}$.

Proof: See Online Appendix B. □

This means that for $\varepsilon > 1$, research is directed to the technically more advanced sector whereas for $\varepsilon < 1$ the less advanced sector is favoured. In addition to the technological level of both sectors, the exogenous energy price affects research incentives. In general, an increasing energy price increases (decreases) the profitability of innovation in the labour-intensive sector for $\varepsilon > 1$ ($\varepsilon < 1$). Whether this effect of the energy price ultimately dominates the direct productivity effect depends on the growth rates of the energy price and the technologies. Analysing the growth rate of the relative profit yields the following lemma:

Lemma 2 *i. With moderate growth of the energy price, i.e. the growth rate remains in the band* $-\eta_l\gamma(1-\alpha)/\alpha_2 \le \gamma_{c_E} \le \eta_e\gamma(1-\alpha_1)/\alpha_2$*, the direction of technical change is determined by relative productivity that dominates the effect of energy price growth.*

ii. Strong growth of the energy price, i.e. $\gamma_{c_E} > \eta_e\gamma(1-\alpha_1)/\alpha_2$*, will ultimately lead to research in the l-(e-) sector for* $\varepsilon > 1$ $(\varepsilon < 1)$.

iii. Strong negative growth of the energy price, i.e. $\gamma_{c_E} < -\eta_l\gamma(1-\alpha)/\alpha_2$*, will ultimately lead to research in the e- (l-) sector only for* $\varepsilon > 1$ $(\varepsilon < 1)$.

Proof: See Online Appendix B. □

Finally, we impose the following three assumptions based on Lemma 1, which will be useful for the subsequent analysis.

Assumption 1 $A_e(t)^{(-\varphi_1)} / A_l(t)^{(-\varphi)} < \kappa c_E(t)^{\alpha_2(\varepsilon-1)}\eta_l / \eta_e$.

Assumption 2 $A_e(t)^{(-\varphi_1)} / A_l(t)^{(-\varphi)} > \kappa c_E(t)^{\alpha_2(\varepsilon-1)}\eta_l / \eta_e$.

Assumption 3 $A_e(t)^{(-\varphi_1)} / A_l(t)^{(-\varphi)} = \kappa c_E(t)^{\alpha_2(\varepsilon-1)}\eta_l / \eta_e$.

Assumption 1 implies that the *l*-sector's technological advancement results in research in the *l*-sector (*e*-sector) only for $\varepsilon > 1$ ($\varepsilon < 1$). Similarly, under Assumption 2 the *e*-sector's sufficient advancement at time *t* induces research in the *e*-sector (*l*-sector) only for $\varepsilon > 1$ ($\varepsilon < 1$). Assumption 3 implies that research is directed to both sectors. For the analysis, we use natural baseline scenarios, namely research directed to one sector only for $\varepsilon > 1$ and research directed to both sectors in case of $\varepsilon < 1$. The intuition follows from Lemma 1. If both sectoral goods are gross substitutes and Assumption 1 holds, research is and will remain directed to the *l*-sector, as research increases the relative profitability of innovation in this sector. Similarly, when Assumption 2 holds, research is directed to the energy-intensive sector only and further increases the profitability of innovation in the *e*-sector.

In contrast, when both goods are gross complements and Assumption 1 holds, i.e. the labour-intensive sector is more advanced, research will be directed to the less advanced *e*-sector as the price effect dominates. Similarly, if Assumption 2 holds, research is directed to the more backward *l*-sector. Hence, ultimately the equilibrium must be characterised by innovation in both sectors.[8]

3 ENERGY INTENSITY DYNAMICS

After characterising the model equilibrium and the determinants of the direction of technological progress, we analyse the energy intensity of the whole economy. We first show that the evolution of the energy intensity can be disaggregated in two driving forces: a *structural effect* and an *efficiency effect*. Subsequently, we analyse direction and magnitude of these effects given energy price growth, technical change in the labour-intensive sector, and technical change in the energy-intensive sector. Finally, we combine these results to examine the energy intensity dynamics in heterogeneous economies that differ with respect to their sectoral productivities and the direction of technical change. In order to simplify notation, the time index t is dropped throughout this section.

3.1 Decomposition into Structural Effect and Efficiency Effect

Defining the energy intensity as total energy input relative to total output, E/Y, and using the production function for the final product (2), the energy intensity of the whole economy can be written as:

$$\frac{E}{Y} = \frac{E}{\left(Y_l^{\frac{\varepsilon-1}{\varepsilon}} + Y_e^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}} = \frac{E}{Y_e}\left(\left(\frac{Y_l}{Y_e}\right)^{\frac{\varepsilon-1}{\varepsilon}} + 1\right)^{\frac{\varepsilon}{1-\varepsilon}}. \tag{11}$$

The growth rate of the energy intensity, $\gamma_{\frac{E}{Y}}$, is obtained by taking logarithms and differentiating with respect to time as

$$\underbrace{\gamma_{\frac{E}{Y}}}_{\text{total effect}} \equiv \frac{d\ln\left(\frac{E}{Y}\right)}{dt} = \underbrace{\gamma_{\frac{E}{Y_e}}}_{\text{efficiency effect}} + \underbrace{\left(-\frac{Y_l^{\frac{\varepsilon-1}{\varepsilon}}}{Y_l^{\frac{\varepsilon-1}{\varepsilon}} + Y_e^{\frac{\varepsilon-1}{\varepsilon}}}\right)\gamma_{\frac{Y_l}{Y_e}}}_{\text{structural effect}}, \tag{12}$$

where $\gamma_{\frac{E}{Y_e}}$ denotes the growth rate of the energy intensity in the energy-intensive sector and $\gamma_{\frac{Y_l}{Y_e}}$ is the growth rate of the labour-intensive sector relative to the energy-intensive sector. As shown in expression (12), the development of the energy intensity can be decomposed into an efficiency effect and a structural effect. The efficiency effect refers to changes in the energy intensity in the *e*-sector, which translate into changes in the energy intensity of the whole economy. The structural effect captures the relative size of the labour-intensive sector. Since this sector does not use any energy for production, an increase of the share of the labour-intensive sector in total production leads, c.p., to a reduction of the economy wide energy intensity.

8. This result is formally derived in Online Appendix B.

Using the previously derived equilibrium values (see Online Appendix A), the strength and direction of the efficiency and the structural effect can be analysed. Using the equilibrium values for energy use and production in the *e*-sector, (A.21) and (A.23), we can analyse how the energy intensity in the *e*-sector is affected by changes of the energy costs as well as changes of the productivity levels in both sectors. The equilibrium energy intensity in the energy-intensive sector is:

$$\frac{E}{Y_e} = \frac{\alpha_2 \alpha^{2\alpha} c_E^{\alpha_2 - 1} A_l^{1-\alpha}}{\left(\left(\alpha^{2\alpha} c_E^{\alpha_2}\right)^{1-\varepsilon} A_l^{\varphi} + \left(\psi^{\alpha_2} (\alpha_1)^{2\alpha_1} (\alpha_2)^{\alpha_2}\right)^{1-\varepsilon} A_e^{\varphi_1}\right)^{-\frac{1}{1-\varepsilon}}}. \tag{13}$$

Taking the logarithms and differentiating with respect to time yields the following expression for the development of the energy intensity in the energy-intensive sector, i.e. the efficiency effect:

$$\textit{efficiency effect} \equiv \gamma_{\frac{E}{Y_e}} = -\left(1-\alpha_2 S\right)\gamma_{c_E} + S\left[(1-\alpha)\gamma_{A_l} - (1-\alpha_1)\gamma_{A_e}\right], \tag{14}$$

with $S \equiv \frac{A^{1-\varepsilon}}{A^{1-\varepsilon} + \theta c_E^{\alpha_2(1-\varepsilon)}} = Y_l^{\frac{\varepsilon-1}{\varepsilon}} / \left(Y_l^{\frac{\varepsilon-1}{\varepsilon}} + Y_e^{\frac{\varepsilon-1}{\varepsilon}}\right) \in (0,1)$, $A \equiv \left(\frac{A_e^{1-\alpha_1}}{A_l^{1-\alpha}}\right)$, $\theta \equiv \left(\frac{\alpha^{2\alpha}}{\psi^{\alpha_2}\alpha_1^{2\alpha_1}\alpha_2^{\alpha_2}}\right)^{1-\varepsilon} > 0$, γ_{c_E} denoting the growth rate of the energy price, and γ_{A_l} (γ_{A_e}) denoting the rate of technical change in the labour-intensive (energy-intensive) sector.

In a next step, we derive the structural effect. Using the equilibrium values for sectoral outputs, (A.22) and (A.23), the relative output of the labour-intensive sector is:

$$\frac{Y_l}{Y_e} = \alpha^{2\alpha\varepsilon} \alpha_1^{-\frac{2\alpha_1}{1-\alpha}(\varepsilon - \varepsilon\alpha} \alpha_2^{-\frac{\alpha_2\varepsilon(1+\alpha)}{1-\alpha}} \psi^{\frac{\alpha_1\alpha_2\varepsilon}{1-\alpha}} A_e^{-\frac{1-\alpha_1}{1-\alpha}(1-\alpha-\varphi)} A_l^{1-\alpha-\varphi} c_E^{\varepsilon\alpha_2}. \tag{15}$$

Taking the logarithms, differentiating with respect to time, and multiplying with $(-S)$ yields the structural effect:

$$\textit{structural effect} \equiv -S \cdot \gamma_{\frac{Y_l}{Y_e}} = S \cdot \varepsilon\left(-\alpha_2\gamma_{c_E} - (1-\alpha)\gamma_{A_l} + (1-\alpha_1)\gamma_{A_e}\right). \tag{16}$$

3.2 The Effects of Technical Change and Energy Price Growth

In order to characterize the effect of technical change and energy price growth on energy intensity dynamics, we substitute the expressions (14) and (16) into (12). This yields the growth rate of the economy wide energy intensity as the sum of the efficiency effect (EE) and the structural effect (SE):

$$\begin{aligned}\gamma_{\frac{E}{Y}} &= [\underbrace{-\left(1-\alpha_2 S\right)}_{\text{EE}} \underbrace{-S\varepsilon\alpha_2}_{\text{SE}}]\gamma_{c_E} + [\underbrace{(1-\alpha)S}_{\text{EE}} \underbrace{-S(1-\alpha)\varepsilon}_{\text{SE}}]\gamma_{A_l} \\ &+ [\underbrace{-(1-\alpha_1)S}_{\text{EE}} \underbrace{+S\varepsilon\left(1-\alpha_1\right)}_{\text{SE}}]\gamma_{A_e}.\end{aligned} \tag{17}$$

This expression for the growth rate of energy intensity (total effect) establishes the following proposition that shows how innovation in the *e*-sector, innovation in the *l*-sector, and energy price growth respectively affect the efficiency and the structural effect.

Proposition 1 *i. Innovation in the e-sector, $\gamma_{A_e} > 0$, leads to a positive structural effect and a negative efficiency effect, where, in the case of $\varepsilon > 1$ ($\varepsilon < 1$), the structural (efficiency) effect dominates the efficiency (structural) effect, i.e. it increases (decreases) the growth rate of energy intensity.*

ii. Innovation in the l-sector, $\gamma_{A_l} > 0$, leads to a negative structural effect and a positive efficiency effect, where, in the case of $\varepsilon > 1$ ($\varepsilon < 1$) the structural (efficiency) effect dominates the efficiency (structural) effect, i.e. it decreases (increases) the growth rate of the energy intensity.

iii. A positive (negative) growth rate of the energy price, $\gamma_{c_E} > 0$ ($\gamma_{c_E} < 0$), leads to a negative (positive) structural effect and a negative (positive) efficiency effect and hence always decreases (increases) the growth rate of the energy intensity.

Proof: See Online Appendix C. ☐

The first part of Proposition 1 (*i*) implies that technical change in the energy-intensive sector, c.p., implies a positive structural effect. The increasing productivity in the energy-intensive sector induces a reallocation of labour towards this sector. Hence, the relative size of the *e*-sector increases over time. This restructuring of the economy towards the energy-intensive sector increases energy intensity (positive structural effect). Furthermore, $\gamma_{A_e} > 0$ implies a negative efficiency effect. Due to the increased productivity of the *e*-sector, the sectoral output grows faster than energy input and hence reduces energy intensity.

According to the first part of Proposition 1 (*ii*), innovation in the labour-intensive sector induces, c.p., an increase in average productivity in the *l*-sector and a reallocation of labour from the *e*- to the *l*-sector. The resulting restructuring of the economy's composition towards the *l*-sector yields a negative structural effect, i.e. a reduction of energy intensity in the economy. The induced decrease in labour input in the *e*-sector causes a substitution of labour by other factors of production, as energy, which, c.p., yields an increase of the energy intensity in the *e*-sector (positive efficiency effect).

In the case of both $\gamma_{A_e} > 0$ and $\gamma_{A_l} > 0$, the structural effect dominates the efficiency effect in the case of substitutes and vice versa for gross complements (second parts of Proposition 1, *i* and *ii*). This result is solely driven by the effect of ε on the structural effect, which is reduced, when both sectors are gross complements. Consider gross complements. As can be seen in the relative demand for both sectoral goods (A.1), an increase of output in the *l*-sector induced by $\gamma_{A_l} > 0$ results in a more than proportional increase of the relative price of the energy-intensive good (p_e / p_l) due to the gross complementarity of both sectors. This price reaction dampens the growth of the *l*-sector and hence the induced structural effect. Similarly, output growth in the *e*-sector induced by $\gamma_{A_e} > 0$ induces a more than proportional increase in the relative price of the labour-intensive good and also dampens the structural effect. In the case of gross substitutes, the structural effect dominates the efficiency effect. In the case of $\gamma_{A_e} > 0$, e.g., this implies that, in spite of technological improvements in the energy-intensive sector, the increase of the share of this sector's output overcompensates the energy saving effect of technical change and hence leads to an increase of the energy intensity. Similarly, for $\gamma_{A_l} > 0$, the reduction of energy intensity induced by the negative structural effect is stronger than the positive efficiency effect.

Finally, Proposition 1 (*iii*) implies that increasing energy prices, c.p., negatively affect both effects independent of the elasticity of substitution. Positive energy price growth induces a substitution of energy by other factors of production in the energy-intensive sector (negative efficiency effect). The reduction of energy use in the *e*-sector reduces the marginal productivity of labour in this sector. Hence, labour is reallocated towards the l-sector, which increases the l-sector's relative size (negative structural effect).

3.3 Combined Results

In this subsection, we now turn to the comprehensive analysis of energy intensity developments. We combine the results from Lemmas 1 and 2 and Proposition 1 to examine the joint effect of energy price growth and technical change on the direction and magnitude of the efficiency and the structural effect. The analysis distinguishes between economies that are technologically more advanced in the labour-intensive and those more advanced in the energy-intensive sector. For both cases, we derive how the development of overall energy intensity (total effect) is affected by efficiency and structural effect and different energy price growth rates. We analyse both the case of gross substitutes, $\varepsilon > 1$, as well gross complements, $\varepsilon < 1$.

Substituting for S in (17) and rearranging yields the growth rate of energy intensity:

$$\gamma_{\frac{E}{Y}} = \left[\frac{\alpha_2(1-\varepsilon)\, A^{1-\varepsilon}}{A^{1-\varepsilon} + \theta c_E^{\alpha_2(1-\varepsilon)}} - 1\right]\gamma_{c_E} + \left[\frac{\varphi\, A^{1-\varepsilon}}{A^{1-\varepsilon} + \theta c_E^{\alpha_2(1-\varepsilon)}}\right]\gamma_{A_l} + \left[\frac{-\varphi_1\, A^{1-\varepsilon}}{A^{1-\varepsilon} + \theta c_E^{\alpha_2(1-\varepsilon)}}\right]\gamma_{A_e}. \tag{18}$$

The expressions for the efficiency effect (14), the structural effect (16), and the total effect (18) are the basis for the following propositions, which identify the direction and magnitude of these effects for different directions of technical change.

Proposition 2 *With research directed to the l-sector only, i.e. Assumption 1 (Assumption 2) holds for $\varepsilon > 1$ ($\varepsilon < 1$), and hence $\gamma_{A_l} = \gamma\eta_l$ and $\gamma_{A_e} = 0$:*

i. The total effect is negative, when

$$\gamma_{c_E} > \frac{\varphi A^{1-\varepsilon}}{\left(\alpha_2(1-\varepsilon)-1\right)A^{1-\varepsilon} - \theta c_E^{\alpha_2(1-\varepsilon)}}\gamma\eta_l \equiv \Lambda_{l,TE} \overset{(<)}{>} 0 \Leftrightarrow \varepsilon \overset{(<)}{>} 1,\ \textit{where}\ \frac{\partial \Lambda_{l,TE}}{\partial A} < 0.$$

ii. The efficiency effect is negative, when $\gamma_{c_E} > \dfrac{(1-\alpha)A^{1-\varepsilon}}{(1-\alpha_2)A^{1-\varepsilon} + \theta c_E^{\alpha_2(1-\varepsilon)}}\gamma\eta_l \equiv \Lambda_{l,EE} > 0,$ *where* $\dfrac{\partial \Lambda_{l,EE}}{\partial A} \overset{(>)}{<} 0$ *for* $\varepsilon \overset{(<)}{>} 1.$

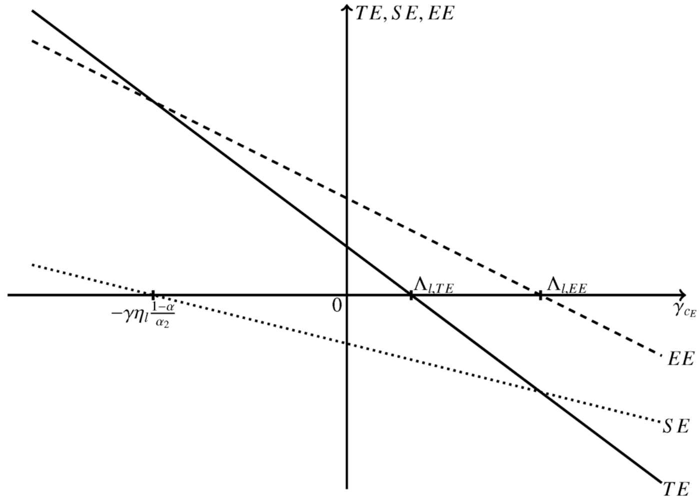
iii. The structural effect is negative, when $\gamma_{c_E} > -\eta_l\gamma(1-\alpha)/\alpha_2$, i.e. strong negative growth of the energy price.

Proof: See Online Appendix C. □

Assume $\varepsilon > 1$ and consider an economy where research is directed entirely to the l-sector, i.e. Assumption 1 holds, and hence Proposition 2 can be applied. In order to illustrate the results, Figure 1 depicts efficiency, structural, and total effect as a function of the energy price growth rate.

The figure shows that energy price growth negatively affects energy intensity development. Furthermore, the evolution of energy intensity is largely driven by the structural effect. As long as the energy price does not decline at a strong rate, the restructuring of the economy away from the energy-intensive sector has a decreasing effect on the overall energy intensity. The efficiency effect becomes negative for all energy price growth rates above the threshold $\Lambda_{l,EE}$. When the energy price grows at a lower rate or even decreases, producers in the energy-intensive sector do not have incentives to reduce energy use. In addition, technical change in the l-sector induces a reallocation of labour towards this sector and hence fosters a substitution of labour by other factors of production,

Figure 1: Efficiency, structural, and total effect for $\varepsilon > 1$ and research directed to the labour-intensive sector.



as energy, in the *e*-sector. The threshold $\Lambda_{l,EE}$ is negatively affected by A. As research is directed to the *l*-sector only, A declines and hence the threshold $\Lambda_{l,EE}$ increases. The intuition is as follows. A higher productivity in the *l*-sector induces a reallocation of labour towards this sector. The reduction of labour in the *e*-sector fosters a substitution away from labour towards other production factors, as energy. Hence, the higher the productivity advantage of the *l*-sector, the higher the energy price growth rate has to be in order to induce a negative efficiency effect. The total effect is negative, when energy price grows at a rate larger than $\Lambda_{l,TE}$.

Proposition 3 *With research directed to the e-sector only, i.e. Assumption 2 (Assumption 1) holds for $\varepsilon > 1$ ($\varepsilon < 1$), and hence $\gamma_{A_l} = 0$ and $\gamma_{A_e} = \gamma\eta_e$:*

i. The total effect is negative, when

$$\gamma_{c_E} > \frac{\varphi_1 A^{1-\varepsilon}}{\left(\alpha_2(1-\varepsilon)-1\right)A^{1-\varepsilon} - \theta c_E^{\alpha_2(1-\varepsilon)}}\gamma\eta_e \equiv \Lambda_{e,TE} \overset{(<)}{>} 0 \Leftrightarrow \varepsilon \overset{(<)}{>} 1, \text{ where } \frac{\partial\Lambda_{e,TE}}{\partial A} < 0.$$

ii. The efficiency effect is negative, when $\gamma_{c_E} > -\dfrac{(1-\alpha_1)A^{1-\varepsilon}}{(1-\alpha_2)A^{1-\varepsilon} + \theta c_E^{\alpha_2(1-\varepsilon)}}\gamma\eta_e \equiv \Lambda_{e,EE} < 0$,

where $\dfrac{\partial\Lambda_{e,EE}}{\partial A} \overset{(<)}{>} 0 \Leftrightarrow \varepsilon \overset{(<)}{>} 1.$

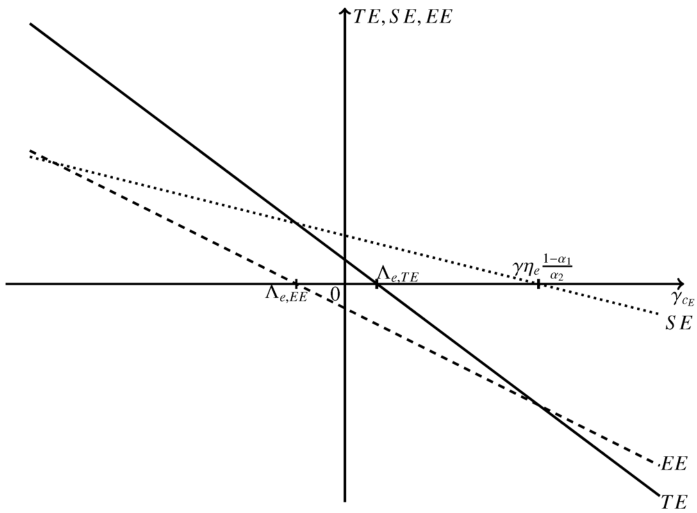
iii. The structural effect is negative, when $\gamma_{c_E} > \eta_e\gamma\left(1-\alpha_1\right)/\alpha_2$, i.e. strong growth of the energy price.

Proof: See Online Appendix C. ☐

In contrast, consider an economy that is more advanced in the energy-intensive sector, i.e. Assumption 2 holds, and research is directed to *e*-sector. In this case, the results of Proposition 3 can be applied, which are illustrated in Figure 2.

Similar to the previous case, the figure clearly shows that the development of energy intensity and both partial effects are negatively affected by the energy price growth rate. In contrast to the case of technical change directed to the *l*-sector, technical change in the energy-intensive sector

Figure 2: Efficiency, structural, and total effect for $\varepsilon > 1$ and research directed to the energy-intensive sector.



induces a structural change of the economy towards the *e*-sector. Hence, the structural effect is positive in this case as long as there is no strong growth of the energy price. In contrast, the efficiency effect is negative for all energy price growth rates above the negative threshold $\Lambda_{e,EE}$ and largely drives the energy intensity development. The threshold itself is positively affected by A, and hence increases, when research is directed to the *e*-sector only. The higher the productivity in the *e*-sector, the more labour is reallocated towards this sector and the more costly it becomes to attract additional labour from the *l*-sector. This increases the incentive for producers in the *e*-sector to substitute away from labour towards other factors of production, as energy. Hence, the higher A, the larger $\Lambda_{e,EE}$ has to be in order to induce a negative efficiency effect. For energy price growth rates above $\Lambda_{e,TE}$, the negative efficiency effect dominates the positive structural effect and hence the total effect is negative.

Comparing the efficiency effects in Figures 1 and 2 illustrates the role of technical change in the *e*-sector. In the case depicted in Figure 1, there is no technical change in the energy-intensive sector. Hence, the negative efficiency effect is solely caused by the substitution of energy by other factors of production, which is only induced by energy price growth above $\Lambda_{l,EE}$. In Figure 2 we can see that even for small negative energy price growth rates the efficiency effect is negative, which is due to the additional effect of technical change in the energy-intensive sector in this case.

For $\varepsilon > 1$, it is important to bear in mind that, as outlined in Lemma 2, a sufficiently strong (negative) energy price growth can ultimately change the direction of research. In the case of an economy, where research is initially directed to the *e*-sector (Proposition 3), strong growth of the energy price will ultimately induce a redirection of innovation towards the labour-intensive sector. This effect can be seen in Figure 2, where the structural effect becomes negative for strong energy price growth. The intuition is as follows. The rapidly growing costs of energy cannot be compensated by innovation. Energy input declines over time and hence the output in the energy-intensive sector shrinks. This means that strong energy price growth fosters a restructuring of the economy towards the *l*-sector even when innovation is still directed to the *e*-sector. As the decline in relative output is stronger than the increase of its relative price, the profitability of innovation in this sector decreases. This process continues until the relative profitability of research in the *e*-sector falls below unity and research switches to the *l*-sector, i.e. Assumption 1 applies. The timing of this switch of research depends, next to the actual magnitude of energy price growth, on the relative productivity of the -sector.[9]

Proposition 4 *Consider* $\varepsilon < 1$.

i. With moderate growth of the energy price growth, i.e. $-\eta_l \gamma \left(1-\alpha\right) / \alpha_2 \leq \gamma_{c_E} \leq \eta_e \gamma \left(1-\alpha_1\right) / \alpha_2$, *and research directed to the both sectors, i.e. Assumption 3 holds, and hence* $\gamma_{A_l} = s_l \gamma \eta_l = \dfrac{\alpha_2(\varepsilon-1)\dfrac{\gamma_{c_E}}{\gamma} + \eta_e \varphi_1}{\eta_e \varphi_1 + \eta_l \varphi} \gamma \eta_l$ *and* $\gamma_{A_e} = s_e \gamma \eta_e = \dfrac{\alpha_2(1-\varepsilon)\dfrac{\gamma_{c_E}}{\gamma} + \eta_l \varphi}{\eta_e \varphi_1 + \eta_l \varphi} \gamma \eta_e$, *the efficiency effect equals* $-\gamma_{c_E}$, *the structural effect equals zero. Hence, the total effect equals* $-\gamma_{c_E}$.

ii. With strong growth of the energy price growth, i.e. $\gamma_{c_E} > \eta_e \gamma \left(1-\alpha_1\right) / \alpha_2$, *and research directed to the e-sector only, i.e. Assumption 1 holds, and hence* $\gamma_{A_l} = 0$ *and* $\gamma_{A_e} = \gamma \eta_e$, *the efficiency effect, the structural effect, and the total effect are negative.*

iii. With strong negative growth of the energy price growth, i.e. $\gamma_{c_E} < -\eta_l \gamma \left(1-\alpha\right) / \alpha_2$, *and research directed to the l-sector only, i.e. Assumption 2 holds, and hence* $\gamma_{A_l} = 0$ *and* $\gamma_{A_e} = \gamma \eta_e$, *the efficiency effect, the structural effect, and the total effect are positive.*

Proof: See Online Appendix C.

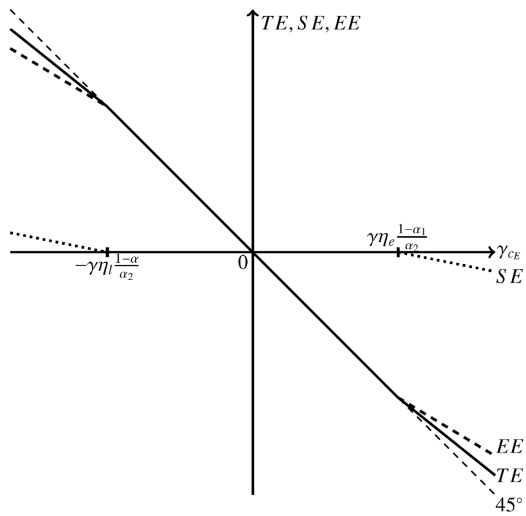
The results of Proposition 4 are illustrated in Figure 3. When research is directed to both sectors, which is the relevant case for moderate energy price growth rates, the relative sector size does not change and hence the structural effect is equal to zero. The evolution of energy intensity is solely driven by the efficiency effect. The higher the energy price growth, the larger the share of scientists directing their research towards the *e*-, which is the typical result of DTC models.[10] This reallocation compensates the increasing growth rate of the energy price such that the relative sector size remains constant (structural effect is zero). Increasing costs of energy induce substitution of energy by other production factors in the energy-intensive sector which leads to a negative efficiency effect. Given the constant relative sector size, this directly translates to a energy intensity reduction in the whole economy. The opposite effects can be observed for moderate negative growth rates of the energy price.

For strong (negative) growth rates of the energy price, research is directed to one sector only. In case of strong energy price growth, i.e. $\gamma_{c_E} > \left(1-\alpha_1\right)\eta_e \gamma / \alpha_2$, all research is directed to the *e*-sector, i.e. Assumption 1 holds. However, technical change in the energy-intensive sector cannot overcompensate the rapidly growing energy costs. This means that strong energy price growth fos-

9. The reverse effect applies for an economy, where research is initially directed to the *l*-sector. In this case, strong negative growth of the energy price will ultimately redirect innovation to the *e*-sector.

10. This can be seen in the expressions for the equilibrium allocation of researchers to the *l*- and the *e*-sector, S_l and S_e, in Proposition 4. As can be seen for $\varepsilon < 1$, S_e increases, when γ_{c_E} decreases, i.e. the higher energy price growth, the more researchers direct their effort towards the energy-intensive sector.

Figure 3: Efficiency, structural, and total effect for $\varepsilon < 1$.



ters a restructuring of the economy towards the *l*-sector even when innovation is still directed to the *e*-sector. Hence, as we can see in Figure 3, the structural effect becomes negative.[11]

Overall, the model results crucially depend on whether ε is larger or smaller than unity, which is a typical attribute of DTC models. Our theoretical results better fit empirical observations for $\varepsilon > 1$. For $\varepsilon < 1$, the structural effect is equal to zero, unless there is a strong positive or negative growth rate of the energy price. However, decomposition analyses show an important role of sectoral adjustments as a driver of energy intensity reductions as they attribute for 25% of energy intensity reduction in OECD countries (Mulder and de Groot, 2012). For gross substitutes, the model predicts an efficiency and a structural effect different from zero for almost any energy price growth rate. The latter results are in line with empirical decomposition studies, that typically find both effects. It is, however, difficult to provide empirical evidence on this elasticity. While there are numerous studies estimating elasticities of substitution between production factors, there are almost no estimates of elasticities of substitution between sectors. Exceptions are Oberfield and Raval (2014), who estimate cross industry elasticities of demand based on US data and overall find values ranging between 0.75 and 2.2, and Edmond et al. (2015), who determine an elasticity of substitution across sectors of 1.24. To our knowledge, however, there are no estimates of the elasticity of substitution between energy-intensive and labour-intensive sectors and an estimation of such an elasticity is out of the scope of this paper. Overall, we consider $\varepsilon > 1$ to be the more plausible assumption, which we will use for the subsequent calibration.

4. CROSS-COUNTRY DIFFERENCES IN ENERGY INTENSITY DYNAMICS

In this section, we present simulations of energy intensity developments and their drivers across countries. The purpose of this exercise is not to provide comprehensive quantitative predictions of energy intensity developments. Our objectives are twofold. First, we illustrate the main results of our theoretical model, i.e. how differences in sectoral productivities and different energy

11. The opposite effects can be observed for strong negative energy price growth. Research is ultimately directed to the *l*-sector only inducing a positive structural effect.

prices between countries affect energy intensity dynamics in the model. Second, we cross-check our results with empirical decomposition studies.

4.1 Calibration

We calibrate the model based on the World Input-Output Database (WIOD, 2013).[12] Our calibration mainly draws from the Environmetal Accounts (EA) and the Socio Economic Accounts (SEA) of the WIOD both covering 34 sectors in 40 countries from 1995–2007/2009. As we explicitly model energy as an input factor in the energy-intensive sector, we drop two energy producing sectors from the WIOD in the calibration, namely *Coke, Refined Petroleum and Nuclear Fuel* (WIOD Code 23) and *Electricity, Gas and Water Supply* (WIOD Code E). An advantage of this data is that it contains consistent information relevant for the calibration. Furthermore, it benefits the cross-checking of our results with the decomposition study of Voigt et al. (2014), which is also based on the WIOD. For the energy price, we use the Indices of Real Energy Prices for Industry from the IEA as they are based on energy prices paid by firms (IEA, 1999; IEA, 2007; IEA, 2008; IEA, 2017).[13] Combining both sources yields a sample of 32 sectors in 26 OECD countries between 1995 and 2007 (see Table 1 in the Appendix for an overview). We calibrate the model based on 1995 data and simulate the development of energy intensities and its drivers until 2007.

As we use a two-sector model, all sectors covered in the WIOD have to be aggregated into two sectors, i.e. an energy-intensive and a labour-intensive sector. We use data on sectoral energy use (EU) in physical units (TJ) from the EA and sectoral gross output (GO) in million USD from the SEA for all 26 countries in order to calculate the aggregate energy intensity for each sector. We calculate the average energy intensity and define all sectors with energy intensities above the average as energy-intensive, while all sectors with energy intensities below the average are aggregated into the labour-intensive sector.

We take $\eta_e = \eta_l = 0.02$ and $\gamma = 1$, which is consistent with a long-run growth rate of 2% (see, e.g., Acemoglu et al. (2012) and Acemoglu et al. (2015)). We follow the standard convention to set the labour share of income to $(1-\alpha) = 2/3$. Hence, a share of $\alpha = 1/3$ is spent on machines (could be interpreted as capital) in the l-sector and on both machines and energy in the e-sector. For the latter sector, we need to also calibrate α_2, which is the energy share of output in the energy-intensive sector. For each country, we derive the energy costs at purchasers' prices in the energy-intensive sector from the World Input-Output Tables of the WIOD.[14] Using the data on sectoral GO, we then calculate the energy cost share in the e-sector for each country, which gives us country-specific proxies of α_2.[15] We further set $\varepsilon = 2$.

Finally, we need to determine the initial sectoral productivities $A_e(t=0)$ and $A_l(t=0)$ for all countries in 1995. While these are difficult to observe, the SEA contain information on sectoral

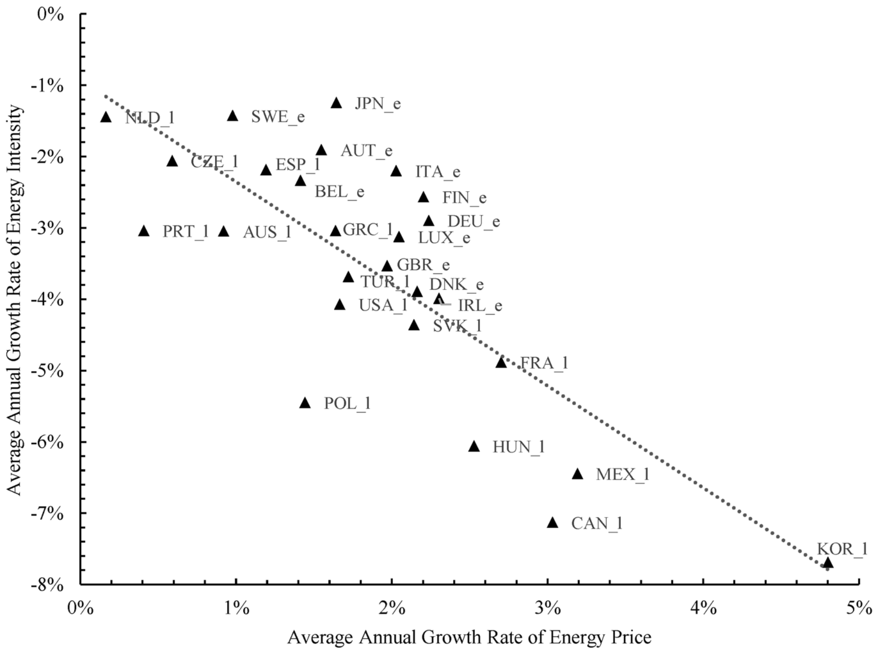
12. We use the 2013 release of the data, which is available at http://www.wiod.org. For detailed information on data sources, construction, and structure of the database see Dietzenbacher et al. (2013), Genty et al. (2012), and Timmer et al. (2015).

13. Similar to our approach, Ley et al. (2016) base their analysis of the effect of energy prices on green innovation on end-use energy prices for the manufacturing sector from IEA.

14. Similar to Kaltenegger et al. (2017), we calculate energy costs as a sum of four cost components: (i) coal, lignite, and peat (CPA10), (ii) crude petroleum and natural gas; services incidental to oil and gas extraction excluding surveying (CPA11), (iii) coke, refined petroleum products and nuclear fuels (CPA23), and (iv) electrical energy, gas, steam and hot water (CPA40).

15. We calibrate α_2 country-specific, as we see quite substantial cross-country differences in the energy cost shares ranging from below 4% to more than 15%.

Figure 4: Correlations between average annual growth rates of energy prices and energy intensities. The subscript *e* (*l*) denotes the direction of technical change towards the *e*-sector (*l*-sector).



employment (total hours worked by persons engaged), which allows us to compute employment in the *l*-sector relative to the *e*-sector. Using the relative employment condition (A.16), we can then set the sectoral productivities to match the observed employment. Hence, also the direction of research is determined for each country.

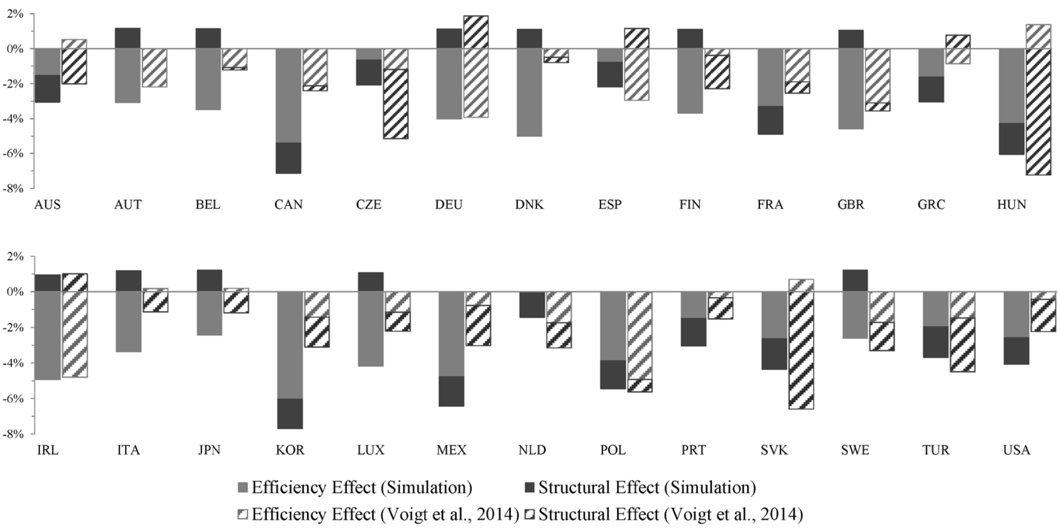
4.2 Results

Given the Parameter choices outlined above, we simulate the efficiency, the structural, and the total effect for all countries in our sample. Figure 4 shows the correlation between the average annual growth rate of energy prices and energy intensity for all 26 countries between 1995–2007. The figure illustrates some core results of the model. The higher the growth rate of the energy price, the stronger is the reduction of energy intensity. The overall reduction of energy intensity seems, on average, larger in countries, where technical change is directed towards the labour-intensive sector.

The results for the efficiency effect and the structural effect are depicted in Figure 5. The figure shows the average annual growth rates for both effects based on our simulation. To cross-check our results, we also calculated the respective growth rates based on the decomposition analysis by Voigt et al. (2014), who cover all 26 countries that we analyse in their decomposition study. Furthermore, they use WIOD data for their analysis, which is the basis for our calibration.

In 11 out of the 26 countries, research is directed towards the energy-intensive sector, i.e. Proposition 3 holds, and hence energy intensity dynamics should be dominated by the efficiency effect. This can be seen, e.g., for Germany. While the structural effect is positive, the efficiency effect is negative. As the growth rate of the energy price is above the threshold $\Lambda_{e,TE}$, the total effect is negative. The restructuring towards the energy-intensive sector induced by innovation in this

Figure 5: Efficiency effect and structural effect—Simulation Results and Results of Voigt et al. (2014)



sector positively affects energy intensity, but is overcompensated by the energy savings within the *e*-sector. In contrast, the USA are an example for an economy that is relatively more advanced in the labour-intensive sector, i.e. Proposition 2 holds. As research is directed to the *l*-sector, we see a negative structural effect in the USA. The efficiency effect is negative as well, which implies an energy price growth rate above the growth rate of the energy price is above the threshold $\Lambda_{l,EE}$.

In both cases, our model's predictions are in line with the decomposition of Voigt et al. (2014). In some cases, our simulation results contradict their results. For Sweden, e.g., our model predicts research to be directed towards the energy-intensive sector resulting in a positive structural and a negative efficiency effect, whereas Voigt et al. (2014) finds a negative structural effect. The opposite discrepancy can be observed for Spain. In the latter case, however, our results are in line with Mulder and de Groot (2012), who find a negative structural effect for Spain in a similar period and hence are in line with our predictions.[16]

Overall, the simulation results of our stylised model seem to be largely consistent with the decomposition studies. To examine the sensitivity of our results, we used different methods to aggregate all available sectors into the energy-intensive and the labour-intensive sector. In a first alternative calibration, we only considered sectors with energy intensities of at least (not more than) 10% above (below) the average as energy-intensive (labour-intensive). We repeated this for 25% and 50%. Hence, going from 10% to 50%, we excluded more sectors that are close to the average of the energy intensity, i.e. we focused more on sectors with very high and those with very low energy intensities. We also used sectoral energy costs per gross output, i.e. sectoral energy cost shares, as an alternative measure to split the sectors into the two groups.[17] Similar to energy intensities, we also stepwise excluded sectors close to the average cost share and repeated the calibration exercise. Overall, the simulation results stayed qualitatively stable compared to our baseline scenario, which we consider to be the most suited for our model.

16. Table 2 in the Appendix depicts an overview of our simulation results, the results of Voigt et al. (2014) and additionally those of Mulder and de Groot (2012), who computed average annual growth rate for all three effects between 1995 and 2005.

17. See footnote 14 for the approach to calculate sectoral energy costs.

5. DISCUSSION

Our model provides insights on the impacts of energy prices and technical change on the development of energy intensity and, in particular, the relative importance of structural adjustments between sectors and energy efficiency improvements within sectors. Furthermore, our model predicts a negative effect of energy price growth on economy-wide energy intensity, which is in line with empirical evidence (Loschel et al., 2015; Metcalf, 2008; Moshiri and Duah, 2016; Popp, 2002). Our simulations illustrate how these two effects predicted by our model vary between countries.

We show that energy intensity reductions are driven by the efficiency effect, when research is directed to the energy-intensive sector, which can be seen in the simulation results for, e.g., Austria or Germany. This efficiency effect is driven by technical change in the *e*-sector as well as factor substitution induced by energy price growth, which is in line with empirical findings. Fisher-Vanden et al. (2016) empirically investigate energy intensive industries and find that higher energy prices and R&D stocks negatively affect energy intensity in these industries. Steinbuks and Neuhoff (2014) analyse various industries and show that the effect of energy price is higher for energy intensive industries and that labour is a substitute for energy. Wang (2013) conducts a decomposition of the efficiency effect in underlying driving forces and shows that technical progress is the the main contributor to energy intensity reductions in Europe. According to Popp (2001), two thirds of the energy savings in energy-intensive industries are due to factor substitution, while one third is due to innovation.

When research is directed to the labour-intensive sector, the model predicts that structural adjustments are a main driver of energy intensity developments. Examples for this case are France or the USA in our simulation exercise. According to our model, the efficiency effect is negative as well if the energy price growth rate is above the positive threshold $\Lambda_{l,EE}$, which is the case for all the countries in our sample. However, the results of the long-run decomposition study by Sue Wing (2008), covering the second half of the 20th century, provide some further evidence on the relationship between $\Lambda_{l,EE}$ and efficiency effect in this case. Sue Wing (2008) decomposes energy intensity in the USA and shows that, in the period between 1958 and the energy price shock 1974–1986, energy price was decreasing and the efficiency effect in the USA was positive. According to our model, the efficiency effect is positive if the energy price growth rate is below the positive threshold $\Lambda_{l,EE}$, which is in line with the empirical evidence. For energy price growth rates below the threshold, there are no incentives to substitute away from energy and hence the efficiency effect is positive. In the period we analyse, the average energy price growth rate is above $\Lambda_{l,EE}$ and hence induces substitution away from energy and resulting in a negative efficiency effect.

We further show that strong (negative) energy price growth may redirect technical change. In our sample, however, we did not observe strong positive or negative growth rates of the energy price.[18] The scenario of strong energy price growth could be applied to the periods of the energy crises and their aftermath (1974–1986) that were characterised by dramatic increases in energy costs (Alpanda and Peralta-Alva, 2010; Linn, 2008; Sue Wing, 2008). In case of gross substitutes, our model predicts stronger energy intensity reductions for strong energy price growth. This finding is in line with, e.g. Sun (1998), who analyses the period 1973–1990 and shows that the reduction in energy intensity was particularly strong in the periods 1973–1980 (14.25%) and 1980–1985 (12.52%). Although this period of strong energy price growth was temporary, it could have redirected technological progress from the energy-intensive to the labour-intensive sector, as outlined in Section 3.

18. The period since the late 1980s, particularly since the late 1990s, has been mainly characterised by moderately growing energy prices (Lee and Lee, 2009; Ley et al., 2016; Narayan and Narayan, 2007; Regnier, 2007).

Our model is highly stylized compared to the complex reality. We used some simplifications in order to identify the effects of energy price and directed technical change on energy intensity dynamics as clearly as possible. Hence, there is room for extensions of our approach. One simplifying assumption we used was an exogenous energy price and did not explicitly model energy generation. We think that this assumption is not too critical, as we do not attempt to do an analysis or predictions for the (very) long run. Furthermore, we interpret the energy price as the final energy price faced by producers including all taxes, which are exogenous from the producers' perspective. According to Sato et al. (2015), the cross-country variation in final industrial energy prices is largely explained by variations in the tax component (e.g., around 60% for electricity and 50%–80% for oil).[19] However, in reality the energy price is not independent of demand. An extension of the model could be to introduce an endogenous energy price by, e.g., introducing resource extraction or an energy production sector. Although we do not model an endogenous energy price, we are able to assess how such an extension would affect our results. In our model, energy price growth induces, e.g., a more efficient use of energy, which does not have any effects on its price. With endogenous energy prices, this price-induced reduction of energy use could in turn dampen the energy price increase. Hence, the introduction of an endogenous energy price in this model would probably reduce the magnitude of the efficiency and structural effects we predict. In order to explicitly analyse the effect of energy taxes/subsidies, the end-use energy price could be split up in a wholesale price and tax/subsidy component ($c_E = c_W + \tau$). Although we assumed the price to implicitly include effects of regulatory instruments, as taxes, we are able to gain some insights on energy-saving policies. A tax on energy, e.g., increases the end-user price of energy and hence negatively affects energy intensity. However, such a policy would mainly work through energy intensity reductions within the energy-intensive sector, which is in line with the findings of Mulder (2015). A redirection of research to the labour-intensive sector would require very high price increases.

For our analysis, we needed a model with at least two sectors that differ in their energy intensity. We followed the majority of the DTC literature by introducing one final good that is assembled from two sectoral goods. This choice, however, does not drive any of the results. The production function for the aggregate output Y could also be interpreted as the households' preferences for sectoral output (Pittel and Bretschger, 2010). To introduce a difference in energy-intensity across sectors, we chose to assume that the productivity of energy in the labour-intensive sector is zero, which reduces the production function of $Y_l(t)$ and hence simplifies the analysis. Such a sectoral structure is commonly used for analyses in two-sector DTC models, where one sector is more energy-, resource-, or emission-intensive than the other (Acemoglu et al., 2012; Daubanes et al., 2013; Di Maria and Valente, 2008; Di Maria and van der Werf, 2008b; Pittel and Bretschger, 2010). This simplifying assumption—energy input is only included in one sector—allows for a clear identification of the efficiency and the structural effect and their driving forces. Of course, one might also think of an alternative and more realistic modelling of this sector structure. A possibility could be to introduce energy input in both sectors, but introduce differences between the sectoral production functions to model the difference in energy intensity, e.g., by assuming energy and other factors to be complements in one sector and substitutes in the other. Such extensions, however, might affect the model's tractability and make it more complex, or even impossible, to analytically decompose energy intensity changes into efficiency and structural effect.

19. Due to this attribute, end-use energy price indices are used as proxies for environmental policy stringency in empirical studies, as Sato and Dechezlepretre (2015) and Aldy and Pizer (2015).

6. CONCLUSION

In this paper, we used a DTC model with an energy-intensive and a labour-intensive sector to analyse the adverse developments of energy intensities across countries. We decomposed energy intensity into a structural effect and an efficiency effect in order to investigate their dynamics due to the direction of research and energy price growth.

Our main contribution to the literature is a first attempt to theoretically analyse the determinants of heterogeneous energy intensity trends based on a dynamic model with endogenous technical change. So far, studies analysing the trends in energy intensities and the interaction of the driving forces, as the structural and efficiency effect, have been empirical. With increasing availability of data and sophisticated methodologies, these studies, particularly those using decomposition methods, have shown extensive and fruitful insights into energy intensity trends that substantially differ across countries. We offer an explanation why structural adjustments drive energy intensity reductions in certain countries whereas they are dominated by within-sector efficiency improvements in others.

We have analysed how energy price growth and the relative productivity of labour- and energy-intensive sectors affect the direction of research and hence the direction and magnitude of the aforementioned two effects. For the case of gross substitutes, we have shown that in economies that are relatively more advanced in the labour-intensive sector, research is directed to this sector and the energy intensity developments are mainly driven by the structural effect. In economies with a relatively more productive energy-intensive sector, the efficiency effect dominates the evolution of energy intensity. When both sectoral goods are gross complements and research is directed to both sectors, energy intensity dynamics are solely driven by the efficiency effect as the relative sector size remains constant. Energy price growth generally negatively affects energy intensity developments and strong positive (negative) growth rates of the energy price can ultimately redirect technical change. Finally, we have calibrated the model to empirical data to illustrate how differences in energy price growth and sectoral productivities affect energy intensity trends across 26 OECD countries. In spite of our very stylised model, the results are largely consistent with empirical studies.

An area of future work might be an empirical investigation of the elasticity of substitution between sectors with high and low energy intensities. As our approach is a first step to theoretically analyse underlying drivers of energy intensity dynamics, extensions or alternative theoretical modelling strategies seem a fruitful direction of further research. In addition to the proposed extensions discussed above, it would be valuable to develop a multi-country model that could be used to analyse between-country structural adjustments caused by international trade, as the data indicates structural adjustments in production between countries. Overall, theoretical research appears to have a potential for important additional insights, as the empirical literature has taught us a great deal about energy intensity developments and its decomposition, whereas the underlying determinants are still largely unexplored.

APPENDIX

Table 1: Sectoral Energy Intensities

Sector	Energy Intensity*
Real Estate Activities (sec70)	0.49
Financial Intermediation (secJ)	0.55
Transport Equipment (sec34t35)	0.79
Electrical and Optical Equipment (sec30t33)	0.81
Renting of M&Eq and Other Business Activities (sec71t74)	0.99
Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles (sec51)	1.03
Machinery, Nec (sec29)	1.10
Leather, Leather and Footwear (sec19)	1.26
Post and Telecommunications (sec64)	1.33
Manufacturing, Nec; Recycling (sec36t37)	1.37
Health and Social Work (secN)	1.45
Education (secM)	1.45
Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel (sec50)	1.57
Construction (secF)	1.70
Rubber and Plastics (sec25)	1.76
Food, Beverages and Tobacco (sec15t16)	1.84
Other Community, Social and Personal Services (secO)	1.95
Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods (sec52)	2.05
Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies (sec63)	2.12
Hotels and Restaurants (secH)	2.21
Textiles and Textile Products (sec17t18)	2.31
Public Admin and Defence; Compulsory Social Security (secL)	3.15
Agriculture, Hunting, Forestry and Fishing (secAtB)	4.43
Wood and Products of Wood and Cork (sec20)	4.69
Pulp, Paper, Paper , Printing and Publishing (sec21t22)	5.18
Inland Transport (sec60)	6.52
Basic Metals and Fabricated Metal (sec27t28)	7.15
Other Non-Metallic Mineral (sec26)	9.10
Mining and Quarrying (secC)	12.28
Chemicals and Chemical Products (sec24)	15.11
Water Transport (sec61)	22.66
Air Transport (sec62)	24.26

* Energy intensity = energy use / gross output, measured in gross energy use in TJ per millions of US.

Table 2: Efficiency, structural, and total effect across countries (average annual growth rates)

	Simulation			Voigt et al. (2014)			Mulder and de Groot (2012)		
Country	EE	SE	TE	EE	SE	TE	EE	SE	TE
AUT	–3.06	1.16	–1.90	–2.18	0.00	–2.18	–0.20	0.40	0.30
BEL	–3.47	1.14	–2.33	–1.08	–0.13	–1.21	–1.10	–0.50	–1.60
CZE	–0.66	–1.40	–2.06	–1.19	–3.97	–5.15	–1.40	0.40	–1.10
DEU	–4.01	1.11	–2.89	–3.92	1.87	–2.06	–2.10	–0.20	–2.40
DNK	–5.00	1.11	–3.89	–0.49	–0.31	–0.80	–1.90	–1.20	–3.20
ESP	–0.78	–1.40	–2.19	–2.95	1.16	–1.80	3.80	–1.10	2.70
FIN	–3.67	1.11	–2.56	–0.38	–1.91	–2.29	–2.60	–1.50	–4.10
FRA	–3.30	–1.58	–4.88	–1.89	–0.66	–2.55	–1.50	–0.50	–2.00
GBR	–4.58	1.05	–3.53	–3.10	–0.46	–3.56	–0.30	–2.10	–2.40
HUN	–4.28	–1.78	–6.06	1.37	–7.24	–5.86	–5.50	–1.10	–6.60
ITA	–3.37	1.17	–2.20	0.17	–1.13	–0.96	–4.80	–0.70	–5.50
JPN	–2.44	1.19	–1.24	0.18	–1.20	–1.02	0.30	–1.30	–1.00
KOR	–6.04	–1.65	–7.69	–1.44	–1.67	–3.11	2.60	–0.40	2.20
NLD	–0.05	–1.39	–1.44	–1.75	–1.41	–3.15	–1.30	–0.30	–1.70
POL	–3.88	–1.57	–5.45	–4.93	–0.69	–5.62	–1.30	0.50	–0.90
SVK	–2.65	–1.71	–4.36	0.69	–6.61	–5.91	–7.20	1.30	–5.80
SWE	–2.62	1.19	–1.42	–1.73	–1.57	–3.31	–1.40	–2.60	–4.00
USA	–2.58	–1.49	–4.07	–0.44	–1.80	–2.24	–3.40	–0.70	–4.10
AUS	–1.54	–1.51	–3.05	0.52	–2.00	–1.48			
CAN	–5.42	–1.71	–7.13	–2.12	–0.29	–2.41			
GRC	–1.62	–1.42	–3.04	–0.86	0.78	–0.09			
IRL	–4.92	0.93	–3.99	–4.80	1.00	–3.80			
LUX	–4.17	1.05	–3.12	–1.15	–1.07	–2.22			
MEX	–4.78	–1.66	–6.44	–0.78	–2.26	–3.03			
PRT	–1.51	–1.53	–3.04	–0.34	–1.18	–1.52			
TUR	–1.98	–1.71	–3.68	–1.47	–3.02	–4.49			

ACKNOWLEDGMENTS

We thank Jana Brandt, Lothar Grall, Matthias Greiff, Jürgen Meckl, Ulf Moslener, Sebastian Voigt, and five anonymous referees for their very helpful inputs. We are grateful for the comments of the participants of the 9th MAGKS Colloquium (Marburg), the Annual Conference 2016 of the Verein für Socialpolitik (Augsburg), the Annual Conference 2017 of the European Association of Environmental and Resource Economists (Athens), and the 15th European Conference of the International Association for Energy Economics (Vienna). Remaining errors are our own.

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Directed Technical Change and Energy Intensity Dynamics: Structural Change vs. Energy Efficiency

Christian Haas, Karol Kempa

Online Technical Appendices

A. SOLVING FOR THE EQUILIBRIUM

In order to simplify notation, we drop the time index in Appendix A. Due to perfect competition on market for the final product, the profit-maximising behaviour of the final good producer results in the following relative demand for both sectoral goods:

$$\frac{p_l}{p_e} = \left(\frac{Y_l}{Y_e}\right)^{-\frac{1}{\epsilon}} . \tag{A.1}$$

This price ratio implies that the relative price is inversely related to the relative supply of both sectors. Defining the final good as numeraire, the price index can be written as

$$\left(p_l^{1-\epsilon} + p_e^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}} = 1. \tag{A.2}$$

Sectoral producers maximise their profits by choosing the quantities of the respective sector specific machines and labour,

$$\max_{x_{li}, L_l} \left\{\Pi_{Y_l} = p_l L_l^{1-\alpha} \int_0^1 A_{li}^{1-\alpha} x_{li}^{\alpha} di - wL_l - \int_0^1 p_{li} x_{li} di\right\}, \tag{A.3}$$

as well as, in the case of the e-sector, the amount of energy,

$$\max_{x_{ei}, L_e, E} \left\{\Pi_{Y_e} = p_e E^{\alpha_2} L_e^{1-\alpha} \int_0^1 A_{ei}^{1-\alpha_1} x_{ei}^{\alpha_1} di - wL_e - \int_0^1 p_{ei} x_{ei} di - c_E E\right\}. \tag{A.4}$$

Profit-maximisation yields the sectoral demands for machine i in the labour-intensive sector,

$$x_{li} = \left(\frac{\alpha p_l}{p_{li}}\right)^{\frac{1}{1-\alpha}} L_l A_{li}, \tag{A.5}$$

and in the energy-intensive sector,

$$x_{ei} = \left(\frac{\alpha_1 p_e E^{\alpha_2} L_e^{1-\alpha}}{p_{ei}}\right)^{\frac{1}{1-\alpha_1}} A_{ei}. \tag{A.6}$$

The demands for machines increase in the price of the respective sector's output (p_j), employed labour in the sector (L_j), and the quality of the individual technology (A_{ji}).

Machines are produced under monopolistic competition. The producer of each variety maximises her profit ($\pi_{ji} = \left(p_{ji} - \psi\right) x_{ji}$) given the demand for her variety. The optimisations yield the price setting rules for monopolists in both sectors, that are $p_{li} = \psi/\alpha$ for machine producers in the l-sector and $p_{ei} = \psi/\alpha_1$ for machine producers in the e-sector. Using these prices and the demands for machines in both sectors, (A.5) and (A.6), the equilibrium profits of machine producers in the labour-intensive sector are

$$\pi_{li} = (1-\alpha)\,\alpha^{\frac{1+\alpha}{1-\alpha}} \left(\frac{1}{\psi}\right)^{\frac{\alpha}{1-\alpha}} p_l^{\frac{1}{1-\alpha}} L_l A_{li}, \tag{A.7}$$

whereas the profits in the energy-intensive sector are

$$\pi_{ei} = (1-\alpha_1)\,\alpha_1^{\frac{1+\alpha_1}{1-\alpha_1}} \left(\frac{1}{\psi^{\alpha_1}}\right)^{\frac{1}{1-\alpha_1}} p_e^{\frac{1}{1-\alpha_1}} E^{\frac{\alpha_2}{1-\alpha_1}} L_e^{\frac{1-\alpha}{1-\alpha_1}} A_{ei}. \tag{A.8}$$

Profit maximisation in the energy-intensive and labour-intensive sectors yields the following first-order conditions:

$$L_l = \left(\frac{w}{(1-\alpha)\,p_l \int_0^1 A_{li}^{1-\alpha} x_{li}^{\alpha} di}\right)^{-\frac{1}{\alpha}}, \tag{A.9}$$

$$L_e = \left(\frac{w}{(1-\alpha)\,p_e E^{\alpha_2} \int_0^1 A_{ei}^{1-\alpha_1} x_{ei}^{\alpha_1} di}\right)^{-\frac{1}{\alpha}}, \text{ and} \tag{A.10}$$

$$E = \left(\frac{c_E}{p_e \alpha_2 L_e^{1-\alpha} \int_0^1 A_{ei}^{1-\alpha_1} x_{ei}^{\alpha_1} di}\right)^{\frac{1}{\alpha_2 - 1}}. \tag{A.11}$$

Plugging the equilibrium quantity of machines (A.5) into (3) yields the production of labour-intensive output:

$$Y_l = L_l A_l \left(\frac{\alpha^2 p_l}{\psi}\right)^{\frac{\alpha}{1-\alpha}}. \tag{A.12}$$

Plugging (A.6) into (A.11) yields the equilibrium quantity of energy:

$$E = \left(\frac{(\alpha_1)^2}{\psi}\right)^{\frac{\alpha_1}{1-\alpha}} \left(\frac{\alpha_2 A_e}{c_E}\right)^{\frac{1-\alpha_1}{1-\alpha}} p_e^{\frac{1}{1-\alpha}} L_e \tag{A.13}$$

Combining (A.13) and (A.6) with (4) yields the production of the energy-intensive good as:

$$Y_e = \left(\frac{(\alpha_1)^2}{\psi}\right)^{\frac{\alpha_1}{1-\alpha}} \left(\frac{\alpha_2 A_e}{c_E}\right)^{\frac{\alpha_2}{1-\alpha}} p_e^{\frac{\alpha}{1-\alpha}} L_e A_e. \tag{A.14}$$

Equilibrium on the labour market implies an identical wage in both sectors. Equating (A.9) and (A.10), together with (A.13), (A.6), and (A.5), yields the relative price:

$$\frac{p_l}{p_e} = \frac{\psi^{\alpha_2} (\alpha_1)^{2\alpha_1} (\alpha_2)^{\alpha_2} A_e^{1-\alpha_1}}{c_E^{\alpha_2} \alpha^{2\alpha} A_l^{1-\alpha}}. \tag{A.15}$$

The relative price (A.1) yields, together with the sectoral production quantities,(A.12) and (A.14), the relative supply in both sectors. Combining relative supply and with relative demands yields the relative employment as:

$$\frac{L_l}{L_e} = \left(\frac{c_E^{\alpha_2} \alpha^{2\alpha}}{\psi^{\alpha_2} (\alpha_1)^{2\alpha_1} (\alpha_2)^{\alpha_2}}\right)^{\epsilon - 1} \frac{A_l^{-\varphi}}{A_e^{-\varphi_1}} \tag{A.16}$$

with $\varphi_1 \equiv (1-\alpha_1)(1-\epsilon)$ and $\varphi \equiv (1-\alpha)(1-\epsilon)$.

Finally, the equilibrium prices and quantities can be calculated. The price ratio (A.15), together with the price index (A.2), leads to the equilibrium prices in both sectors:

$$p_l = \frac{\psi^{\alpha_2}\alpha_1^{2\alpha_1}\alpha_2^{\alpha_2}A_e^{1-\alpha_1}}{\left(\left(\alpha^{2\alpha}c_E^{\alpha_2}\right)^{1-\epsilon}A_l^{\varphi}+\left(\psi^{\alpha_2}\alpha_1^{2\alpha_1}\alpha_2^{\alpha_2}\right)^{1-\epsilon}A_e^{\varphi_1}\right)^{\frac{1}{1-\epsilon}}}, \tag{A.17}$$

$$p_e = \frac{\alpha^{2\alpha}c_E^{\alpha_2}A_l^{1-\alpha}}{\left(\left(\alpha^{2\alpha}c_E^{\alpha_2}\right)^{1-\epsilon}A_l^{\varphi}+\left(\psi^{\alpha_2}\alpha_1^{2\alpha_1}\alpha_2^{\alpha_2}\right)^{1-\epsilon}A_e^{\varphi_1}\right)^{\frac{1}{1-\epsilon}}}. \tag{A.18}$$

Combining the prices with input demands yields the equilibrium employment of labour in both sectors

$$L_l = \frac{\left(\psi^{\alpha_2}\alpha_1^{2\alpha_1}\alpha_2^{\alpha_2}\right)^{1-\epsilon}A_e^{\varphi_1}}{\left(\left(\alpha^{2\alpha}c_E^{\alpha_2}\right)^{1-\epsilon}A_l^{\varphi}+\left(\psi^{\alpha_2}\alpha_1^{2\alpha_1}\alpha_2^{\alpha_2}\right)^{1-\epsilon}A_e^{\varphi_1}\right)}, \tag{A.19}$$

$$L_e = \frac{\left(c_E^{\alpha_2}\alpha^{2\alpha}\right)^{1-\epsilon}A_l^{\varphi}}{\left(\left(\alpha^{2\alpha}c_E^{\alpha_2}\right)^{1-\epsilon}A_l^{\varphi}+\left(\psi^{\alpha_2}\alpha_1^{2\alpha_1}\alpha_2^{\alpha_2}\right)^{1-\epsilon}A_e^{\varphi_1}\right)} \tag{A.20}$$

as well as equilibrium energy use in the energy-intensive sector

$$E = \frac{\left(\frac{\alpha_1^2}{\psi}\right)^{\frac{\alpha_1}{1-\alpha}}\alpha_2^{\frac{1-\alpha_1}{1-\alpha}}\alpha^{2\alpha\left(\frac{1}{1-\alpha}-\epsilon+1\right)}c_E^{\alpha_2-1-\epsilon\alpha_2}A_l^{1+\varphi}A_e^{\frac{1-\alpha_1}{1-\alpha}}}{\left(\left(\alpha^{2\alpha}c_E^{\alpha_2}\right)^{1-\epsilon}A_l^{\varphi}+\left(\psi^{\alpha_2}\alpha_1^{2\alpha_1}\alpha_2^{\alpha_2}\right)^{1-\epsilon}A_e^{\varphi_1}\right)^{\frac{1+\varphi}{\varphi}}}. \tag{A.21}$$

Plugging these optimal inputs into (A.12) and (A.14) yields the the equilibrium outputs in the labour- and energy-intensive sector as

$$Y_l = \frac{\alpha^{\frac{2\alpha}{1-\alpha}}\psi^{\frac{\alpha_1(\epsilon\alpha_2-1)}{1-\alpha}}\alpha_1^{\frac{2\alpha_1(1-\epsilon+\epsilon\alpha)}{1-\alpha}}\alpha_2^{\frac{\alpha_2(1-\epsilon-\epsilon\alpha)}{1-\alpha}}A_e^{\frac{1-\alpha_1}{1-\alpha}(\alpha+\varphi)}A_l}{\left(\left(\alpha^{2\alpha}c_E^{\alpha_2}\right)^{1-\epsilon}A_l^{\varphi}+\left(\psi^{\alpha_2}\alpha_1^{2\alpha_1}\alpha_2^{\alpha_2}\right)^{1-\epsilon}A_e^{\varphi_1}\right)^{\frac{\alpha+\varphi}{\varphi}}}, \tag{A.22}$$

$$Y_e = \frac{\left(\frac{\alpha_1^2}{\psi}\right)^{\frac{\alpha_1}{1-\alpha}}\alpha_2^{\frac{\alpha_2}{1-\alpha}}\alpha^{2\alpha\left(\frac{1}{1-\alpha}-\epsilon\right)}c_E^{-\epsilon\alpha_2}A_l^{\alpha+\varphi}A_e^{\frac{1-\alpha_1}{1-\alpha}}}{\left(\left(\alpha^{2\alpha}c_E^{\alpha_2}\right)^{1-\epsilon}A_l^{\varphi}+\left(\psi^{\alpha_2}\alpha_1^{2\alpha_1}\alpha_2^{\alpha_2}\right)^{1-\epsilon}A_e^{\varphi_1}\right)^{\frac{\alpha+\varphi}{\varphi}}}. \tag{A.23}$$

B. EQUILIBRIUM PROFIT RATIO AND ALLOCATION OF RESEARCHERS

B.1 Relative Profitability of Research

Since scientists only direct a sector and are randomly allocated to a specific machine variety, the average sectoral productivity is used as defined in (5). Combining (A.7) and (A.8) and taking into account the probabilities of a successful innovation, η_j, the expected firm value (i.e. expected profit) of an innovation in the l-sector, $\Pi_l(t)$, relative to an innovation in the e-sector, $\Pi_e(t)$, is:

$$\frac{\Pi_l(t)}{\Pi_e(t)} = \omega \frac{\eta_l}{\eta_e} \cdot \underbrace{\frac{p_l(t)^{\frac{1}{1-\alpha}}}{p_e(t)^{\frac{1}{1-\alpha_1}}}}_{\text{price effect}} \cdot \underbrace{\frac{L_l(t)}{E(t)^{\frac{\alpha_2}{1-\alpha_1}} L_e(t)^{\frac{1-\alpha}{1-\alpha_1}}}}_{\text{market size effect}} \cdot \underbrace{\frac{A_l(t)}{A_e(t)}}_{\substack{\text{direct} \\ \text{productivity effect}}} \tag{B.1}$$

with $\omega \equiv (1-\alpha)\,\alpha^{\frac{1+\alpha}{1-\alpha}}\,(1-\alpha_1)^{-1}\,\alpha_1^{-\frac{1+\alpha_1}{1-\alpha_1}}\,\psi^{\frac{\alpha+\alpha_1}{(1-\alpha)(1-\alpha_1)}}$. Analogously to the Directed Technical Change literature (Acemoglu, 1998, 2002), relative profitability of innovating is affected by a price- and a market size effect. The *price effect* directs innovation in the sector with the higher price. The *market size effect* makes innovations more attractive in the sector, where more factors of production, labour and energy, are employed. Since a larger market size is associated with a lower price for the output of the respective sector, both effects are opposite forces. Finally, the term $A_l(t)/A_e(t)$ captures a *direct productivity effect* as introduced by Acemoglu et al. (2012). This effect directs innovation to the sector that is technologically further advanced and hence follows the concept of "building on the shoulders of giants". In addition to these three forces, the respective probabilities of successful research, η_l and η_e, affect the relative profits.

B.2 Allocation of Researchers

With strong positive (negative) energy price growth, i.e. $\eta_e\gamma\,(1-\alpha_1)\,/\alpha_2 < \gamma_{c_E} < (-\eta_l\gamma\,(1-\alpha)\,/\alpha_2)$, the direction of the change of relative profit is independent of research.

Proof: For $\epsilon > 1$, it follows with (8), (9), and (10) that,

$$\frac{d\left(\frac{\Pi_l(t)}{\Pi_e(t)}\right)}{dt} = \alpha_2(\epsilon-1)\gamma_{c_E} + \varphi_1 s_e \eta_e \gamma - \varphi s_l \eta_l \gamma > 0 \;\Leftrightarrow\; \gamma_{c_e} > \eta_e\gamma(1-\alpha_1)/\alpha_2$$

and

$$\frac{d\left(\frac{\Pi_l(t)}{\Pi_e(t)}\right)}{dt} = \alpha_2(\epsilon-1)\gamma_{c_E} + \varphi_1 s_e \eta_e \gamma - \varphi s_l \eta_l \gamma < 0 \;\Leftrightarrow\; \gamma_{c_e} < -\eta_l\gamma(1-\alpha)/\alpha_2.$$

□

From that it follows that for moderate energy price growth, i.e. $-\eta_l\gamma\,(1-\alpha)\,/\alpha_2 \le \gamma_{c_E} \le \eta_e\gamma\,(1-\alpha_1)\,/\alpha_2$, the direction of the change of relative profit is not independent of research.

Moderate energy price growth

In the case of substitutes ($\epsilon > 1$):

1. From equation (10) and with $s(t) \equiv s_l(t)$ it follows that

$$d\frac{\Pi_{li(t)}}{\Pi_{ei(t)}}/dt \gtreqless 0 \quad \text{if} \quad s(t) \gtreqless \frac{\alpha_2(\epsilon-1)\frac{\gamma_{c_E}}{\gamma} + \eta_l\varphi_1}{\varphi\eta_l + \varphi_1\eta_e} \equiv s^{**}. \tag{B.2}$$

Proof:

$$d\frac{\Pi_{li(t)}}{\Pi_{ei(t)}}/dt \gtreqless 0 \Leftrightarrow 0 \lesseqgtr \frac{d\frac{\Pi_{li(t)}}{\Pi_{ei(t)}}/dt}{\frac{\Pi_{li(t)}}{\Pi_{ei(t)}}} = \frac{\alpha_2(\epsilon-1)}{c_E(t)}\frac{dc_E(t)}{dt} - \frac{\varphi}{A_l(t)}\frac{dA_l(t)}{dt} + \frac{\varphi_1}{A_e(t)}\frac{dA_e(t)}{dt}.$$

Using equation (8) and (9) yields:

$$0 \lesseqgtr \alpha_2(\epsilon-1)\gamma_c - \varphi s_l(t)\gamma\eta_l + \varphi_1 s_e(t)\gamma\eta_e$$
$$\Leftrightarrow s(t) \gtreqless \frac{\alpha_2(\epsilon-1)\frac{\gamma_{c_E}}{\gamma} + \eta_l\varphi_1}{\varphi\eta_l + \varphi_1\eta_e} \equiv s^{**}.$$

□

2. At time $t = z$ there exists a unique equilibrium research allocation $s^*(t = z)$ with research directed to sector l (e) only, i.e. $s(t = z) = 1$ ($s(t = z) = 0$), if

$$A(t=z) \equiv \frac{A_e(t=z)^{(1-\alpha_1)}}{A_l(t=z)^{(1-\alpha)}} \overset{(>)}{<} \left(\frac{\eta_e}{\kappa\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}\right)^{\frac{1}{\epsilon-1}}.$$

Proof: Using equation (10) yields:

$$\frac{\Pi_l(t)}{\Pi_e(t)} = \kappa\frac{\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}{\eta_e}\frac{A_l(t)^{-\varphi}}{A_e(t)^{-\varphi_1}} \overset{(<)}{>} 1 \Leftrightarrow \left(\frac{\eta_e}{\kappa\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}\right)^{\frac{1}{\epsilon-1}} \overset{(<)}{>} \frac{A_e(t)^{(1-\alpha_1)}}{A_l(t)^{(1-\alpha}} \equiv A(t).$$

□

If $s^*(t = z) \in \{0, 1\}$ is an equilibrium in $t = z$ than it is also an equilibrium in all $t > z$ (follows from (B.2)).

3. At time $t = z$ there exist multiple equilibria $s \in [0, 1]$ if

$$A(t=z) = \left(\frac{\eta_e}{\kappa\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}\right)^{\frac{1}{\epsilon-1}}.$$

Proof:

$$\frac{\Pi_l(t)}{\Pi_e(t)} = \kappa\frac{\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}{\eta_e}\frac{A_l(t)^{-\varphi}}{A_e(t)^{-\varphi_1}} = 1 \Leftrightarrow \left(\frac{\eta_e}{\kappa\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}\right)^{\frac{1}{\epsilon-1}} = \frac{A_e(t)^{(1-\alpha_1)}}{A_l(t)^{(1-\alpha}} \equiv A(t).$$

□

If $s^*(t = z) \in (0, 1)$ is an equilibrium in $t = z$ then $s^*(t = z) \in (0, 1)$ is also an equilibrium in $t > z$ if and only if $s^*(t) = s^{**}\ \forall\ t \geq z$. If $s^*(t) \overset{(<)}{>} s^{**}$ there will be research in sector l (e) only in all $t > z$ (follows from (B.2)).

In the case of complements ($\epsilon < 1$):

1. From equation (10) follows:

$$d\frac{\Pi_{li(t)}}{\Pi_{ei(t)}}/dt \gtreqless 0 \quad \text{if} \quad s(t=z) \lesseqgtr s^{**}.$$

Proof: Analogue to the case of substitutes ($\epsilon > 1$) and moderate energy price growth. □

2. At time $t = z$ there exists a unique equilibrium research allocation s^* with research directed to sector l (e) only, i.e. $s(t = z) = 1$ ($s(t = z) = 0$), if

$$A(t=z) \overset{(<)}{>} \left(\frac{\eta_e}{\kappa\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}\right)^{\frac{1}{\epsilon-1}}.$$

Proof: See proof for $\epsilon > 1$ and moderate energy price growth. □

With $s^*(t = z) \in \{0, 1\}$, $\left|1 - \frac{\Pi_{li(t)}}{\Pi_{ei(t)}}\right|$ decreases over time and hence there exists a time $\tau > z$, where $\frac{\Pi_{li(t=\tau)}}{\Pi_{ei(t=\tau)}} = 1 \left(\Leftrightarrow A(t = \tau) = \left(\frac{\eta_e}{\kappa\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}\right)^{\frac{1}{\epsilon}-1}\right)$.

3. At time $t = z$ there exist multiple equilibria $s^* \in [0, 1]$, if

$$A(t = z) = \left(\frac{\eta_e}{\kappa\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}\right)^{\frac{1}{\epsilon-1}}.$$

If $s^*(t = z) \in (0, 1)$ is an equilibrium in $t = z$ than $s^*(t = z) \in (0, 1)$ is also an equilibrium in all $t > z$ if and only if $s^*(t) = s^{**}\ \forall\ t \geq z$.
We assume $s^* = s^{**}$ (i.e. the dynamically stable equilibrium) in the case of an inner equilibrium. This is also the technical result for longer patent duration (see Appendix D).

Strong energy price growth

In the case of substitutes ($\epsilon > 1$):

1. At time $t = z$ there exists a unique equilibrium research allocation $s^*(t = z)$ with research directed to sector l (e) only, i.e. $s(t = z) = 1$ ($s(t = z) = 0$), if

$$A(t = z) = \frac{A_e(t = z)^{(1-\alpha_!)}}{A_l(t = z)^{(1-\alpha}} \overset{(>)}{<} \left(\frac{\eta_e}{\kappa\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}\right)^{\frac{1}{\epsilon}-1}. \tag{B.3}$$

Proof: Using equation (10) yields:

$$\frac{\Pi_l(t)}{\Pi_e(t)} = \kappa\frac{\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}{\eta_e}\frac{A_l(t)^{-\varphi}}{A_e(t)^{-\varphi_1}} \overset{(<)}{>} 1 \Leftrightarrow \left(\frac{\eta_e}{\kappa\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}\right)^{\frac{1}{\epsilon-1}} \overset{(<)}{>} \frac{A_e(t)^{(1-\alpha_!)}}{A_l(t)^{(1-\alpha}} \equiv A(t).$$

□

If $A(t = z) \overset{(>)}{<} \left(\frac{\eta_e}{\kappa\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}\right)^{\frac{1}{\epsilon-1}}$ and with strong positive (negative) energy price growth, $s^*(t = z) = 1$ (0) is an equilibrium in $t = z$ and in all $t > z$ (follows from Lemma 2). If $A(t = z) \overset{(<}{>} \left(\frac{\eta_e}{\kappa\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}\right)^{\frac{1}{\epsilon-1}}$ and with strong positive (negative) energy price growth, $s^*(t = z) = 0$ (1) is an equilibrium in $t = z$ and since $\left|1 - \frac{\Pi_{li(t)}}{\Pi_{ei(t)}}\right|$ increases over time, there exists a time $\tau > z$, such that $\frac{\Pi_{li(t=\tau)}}{\Pi_{ei(t=\tau)}} = 1$ and $\frac{\Pi_{li(t)}}{\Pi_{ei(t)}} \overset{(<)}{>} 1$ for all $t > \tau$, leading to an equilibrium with research directed only to sector l (e) for all $t > \tau$.

2. At time $t = z$ there exist multiple equilibria $s \in [0, 1]$ if

$$A(t = z) = \left(\frac{\eta_e}{\kappa\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}\right)^{\frac{1}{\epsilon-1}}.$$

Proof:

$$\frac{\Pi_l(t)}{\Pi_e(t)} = \kappa\frac{\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}{\eta_e}\frac{A_l(t)^{-\varphi}}{A_e(t)^{-\varphi_1}} = 1 \Leftrightarrow \left(\frac{\eta_e}{\kappa\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}\right)^{\frac{1}{1-\epsilon}} = \frac{A_e(t)^{(1-\alpha_1)}}{A_l(t)^{(1-\alpha}} \equiv A(t).$$

□

With strong positive (negative) energy price growth, $s^*(t) = 1$ ($= 0$) is the unique equilibrium in all $t > z$ (follows from Lemma 2).

In the case of complements ($\epsilon < 1$):

1. At time $t = z$ there exists a unique equilibrium research allocation $s^*(t = z)$ with all research directed to sector l (e), i.e. $s(t = z) = 1$ ($s(t = z) = 0$), if

$$A(t = z) \overset{(>)}{<} \left(\frac{\eta_e}{\kappa\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}\right)^{\frac{1}{\epsilon-1}}. \tag{B.4}$$

If $A(t = z) \overset{(>)}{<} \left(\frac{\eta_e}{\kappa\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}\right)^{\frac{1}{\epsilon-1}}$ and with strong positive (negative) energy price growth, $s^*(t = z) = 0$ (1) is an equilibrium in $t = z$ and in all $t > z$ (follows from Lemma 2). If $A(t = z) \overset{(<}{>} \left(\frac{\eta_e}{\kappa\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}\right)^{\frac{1}{\epsilon-1}}$ and with strong positive (negative) energy price growth, $s^*(t = z) = 1$ (0) is a unique equilibrium in $t = z$ and since $\left|1 - \frac{\Pi_{li(t)}}{\Pi_{ei(t)}}\right|$ increases over time, there exists a time $\tau > z$, such that $\frac{\Pi_{li(t=\tau)}}{\Pi_{ei(t=\tau)}} = 1$ and $\frac{\Pi_{li(t)}}{\Pi_{ei(t)}} \overset{(<)}{>} 1$ for all $t > \tau$, leading to an equilibrium with all research directed to sector l (e) for all $t > \tau$.

2. At time $t = z$ there exist multiple equilibria $s^* \in [0, 1]$, if

$$A(t = z) = \left(\frac{\eta_e}{\kappa\eta_l c_E(t)^{\alpha_2(\epsilon-1)}}\right)^{\frac{1}{\epsilon-1}}.$$

With strong positive (negative) energy price growth, $s^*(t) = 0$ ($= 1$) is the unique equilibrium in all $t > z$ (follows from (B.4)).

C. STRUCTURAL EFFECT AND EFFICIENCY EFFECT

Proof of Proposition 1

$$\gamma_{\frac{E}{Y}} = [(\alpha_2 S - 1) - S\epsilon\alpha_2]\gamma_{c_E} + [(1-\alpha)S - S(1-\alpha)\epsilon]\gamma_{A_l} + [-(1-\alpha_1)S + S\epsilon(1-\alpha_1)]\gamma_{A_e}$$

Proof:

i. Follows from equation (17) with $\gamma_{A_e} > 0$, $\gamma_{A_l} = 0$, and $\gamma_{c_E} = 0$:

$$\begin{aligned} \textit{structural effect} &= (1-\alpha_1)S\epsilon\gamma_{A_e} > 0, \\ \textit{efficiency effect} &= -(1-\alpha_1)S\gamma_{A_e} < 0, \\ \textit{structural effect} + \textit{efficiency effect} \equiv \gamma_{\frac{E}{Y}} &= (\epsilon - 1)(1-\alpha_1)S\gamma_{A_e} \overset{(<)}{>} 0 \Leftrightarrow \epsilon \overset{(<)}{>} 1 \end{aligned}$$

ii. Follows from equation (17) with $\gamma_{A_e} = 0$, $\gamma_{A_l} > 0$, and $\gamma_{c_E} = 0$:

$$\begin{aligned} \textit{structural effect} &= -(1-\alpha)S\epsilon\gamma_{A_l} < 0, \\ \textit{efficiency effect} &= (1-\alpha)S\gamma_{A_l} > 0, \\ \textit{structural effect} + \textit{efficiency effect} \equiv \gamma_{\frac{E}{Y}} &= (1-\epsilon)(1-\alpha)S\gamma_{A_l} \overset{(>)}{<} 0 \Leftrightarrow \epsilon \overset{(<)}{>} 1 \end{aligned}$$

iii. Follows from equation (17) with $\gamma_{A_e} = 0$, $\gamma_{A_l} = 0$, and $\gamma_{c_E} \neq 0$:

$$\begin{aligned} \textit{structural effect} &= -S\epsilon\alpha_2\gamma_{c_E} \overset{(>)}{<} 0 \Leftrightarrow \gamma_{c_E} \overset{(<)}{>} 0, \\ \textit{efficiency effect} &= -(1-\alpha_2 S)\gamma_{c_E} \overset{(>)}{<} 0 \Leftrightarrow \gamma_{c_E} \overset{(<)}{>} 0, \\ \textit{structural effect} + \textit{efficiency effect} \equiv \gamma_{\frac{E}{Y}} &\overset{(>)}{=<} 0 \Leftrightarrow \gamma_{c_E} \overset{(<)}{>} 0. \end{aligned}$$

□

Proof of Proposition 2

Proof:

i. Follows from equation (18):

$$\begin{aligned} \textit{total effect} &= \left[\frac{\alpha_2(1-\epsilon)\,A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}} - 1\right]\gamma_{c_E} + \left[\frac{\varphi\,A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\right]\gamma\eta_l < 0 \\ &\Leftrightarrow \gamma_{c_E} > \frac{\varphi A^{1-\epsilon}}{(\alpha_2(1-\epsilon)-1)\,A^{1-\epsilon} - \theta c_E^{\alpha_2(1-\epsilon)}}\gamma\eta_l \equiv \Lambda_{l,TE} \overset{(<)}{>} 0 \Leftrightarrow \epsilon \overset{(<)}{>} 1, \end{aligned}$$

$$\frac{\partial \Lambda_{l,TE}}{\partial A} = -\frac{(1-\epsilon)\varphi A^{-\epsilon}\theta c_E^{\alpha_2(1-\epsilon)}}{\left[(\alpha_2(1-\epsilon)-1)\,A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}\right]^2}\gamma\eta_e < 0.$$

ii. Follows from equation (14):

$$\begin{aligned} \textit{efficiency effect} &= \frac{(\alpha_2-1)A^{1-\epsilon}-\theta c_E^{\alpha_2(1-\epsilon)}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\gamma_{c_E} + \frac{(1-\alpha)A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\gamma\eta_l < 0, \\ &\Leftrightarrow \gamma_{c_E} > \frac{(1-\alpha)A^{1-\epsilon}}{(1-\alpha_2)A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\gamma\eta_l \equiv \Lambda_{l,EE} > 0. \end{aligned}$$

$$\frac{\partial \Lambda_{l,EE}}{\partial A} = \frac{\varphi A^{-\epsilon}\theta c_E^{\alpha_2(1-\epsilon)}}{\left[(1-\alpha_2)A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}\right]^2}\gamma\eta_l \overset{(>)}{<} 0 \Leftrightarrow \epsilon \overset{(<)}{>} 1.$$

iii. Follows from equation (16):

$$\textit{structural effect} = \frac{A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\epsilon(-\alpha_2\gamma_{c_E}-(1-\alpha)\gamma\eta_l) < 0 \Leftrightarrow \gamma_{c_E} > -\frac{(1-\alpha)}{\alpha_2}\eta_l\gamma.$$

□

Proof of Proposition 3

Proof:

i. Follows from equation (18):

$$\textit{total effect} = \left[\frac{\alpha_2(1-\epsilon)\,A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}-1\right]\gamma_{c_E}+\left[\frac{-\varphi_1\,A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\right]\gamma\eta_e<0$$

$$\Leftrightarrow \gamma_{c_E} > \frac{\varphi_1 A^{1-\epsilon}}{(\alpha_2(1-\epsilon)-1)\,A^{1-\epsilon}-\theta c_E^{\alpha_2(1-\epsilon)}}\gamma\eta_e \equiv \Lambda_{e,TE} \overset{(<)}{>} 0 \Leftrightarrow \epsilon \overset{(<)}{>} 1,$$

$$\frac{\partial\Lambda_{e,TE}}{\partial A} = -\frac{(1-\epsilon)\varphi_1 A^{-\epsilon}\theta c_E^{\alpha_2(1-\epsilon)}}{\left[(\alpha_2(1-\epsilon)-1)\,A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}\right]^2}\gamma\eta_e<0.$$

ii. Follows from equation (14):

$$\textit{efficiency effect} = \left[\frac{\alpha_2\,A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}-1\right]\gamma_{c_E}+\left[\frac{-(1-\alpha_1)\,A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\right]\gamma\eta_e<0$$

$$\Leftrightarrow \gamma_{c_E} > -\frac{(1-\alpha_1)A^{1-\epsilon}}{(1-\alpha_2)A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\gamma\eta_e \equiv \Lambda_{e,EE}<0,$$

$$\frac{\partial\Lambda_{e,EE}}{\partial A} = -\frac{\varphi_1 A^{-\epsilon}\theta c_E^{\alpha_2(1-\epsilon)}}{\left[(1-\alpha_2)A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}\right]^2}\gamma\eta_e \overset{(<)}{>} 0 \Leftrightarrow \epsilon \overset{(<)}{>} 1.$$

iii. Follows from equation (16):

$$\textit{structural effect} = \left[-\frac{\epsilon\alpha_2 A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\right]\gamma_{c_E}+\left[\frac{\epsilon\,(1-\alpha_1)\,A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\right]\gamma\eta_e<0 \Leftrightarrow \gamma_{c_E} > \frac{(1-\alpha_1)}{\alpha_2}\eta_e\gamma.$$

□

Proof of Proposition 4

Proof:

i. Follows from (16):

$$\begin{aligned}\textit{structural effect} =& -\frac{A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\epsilon\alpha_2\gamma_{c_E}-\frac{A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}(1-\alpha)\epsilon\gamma\eta_l\frac{\alpha_2(\epsilon-1)\frac{\gamma_{c_E}}{\gamma}+\eta_e\varphi_1}{\eta_e\varphi_1+\eta_l\varphi}\\ &+\frac{A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\epsilon(1-\alpha_1)\gamma\eta_e\frac{-\alpha_2(\epsilon-1)\frac{\gamma_{c_E}}{\gamma}+\eta_l\varphi}{\eta_e\varphi_1+\eta_l\varphi}\\ =& -\frac{A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\epsilon\alpha_2\gamma_{c_E}+\frac{A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\alpha_2\epsilon\gamma_{c_E}\frac{(1-\alpha)\eta_l+(1-\alpha_1)\eta_e}{\eta_l(1-\alpha)+\eta_e(1-\alpha_1)}\\ &+\frac{A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\epsilon\gamma\frac{(1-\alpha)\eta_l\eta_e(1-\alpha_1)-(1-\alpha_1)\eta_e\eta_l(1-\alpha)}{\eta_l(1-\alpha)+\eta_e(1-\alpha_1)}\\ =&0.\end{aligned}$$

Follows from (14):

$$\begin{aligned}
\textit{efficiency effect} =& \left(\alpha_2 \frac{A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}} - 1\right)\gamma_{c_E} + (1-\alpha)\frac{A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\gamma\eta_l \frac{\alpha_2(\epsilon-1)\frac{\gamma_{c_E}}{\gamma}+\eta_e\varphi_1}{\eta_e\varphi_1+\eta_l\varphi} \\
& - (1-\alpha_1)\frac{A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\gamma\eta_e \frac{-\alpha_2(\epsilon-1)\frac{\gamma_{c_E}}{\gamma}+\eta_l\varphi}{\eta_e\varphi_1+\eta_l\varphi} \\
=& \left(\alpha_2 \frac{A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}} - 1\right)\gamma_{c_E} + \frac{(-1)(1-\alpha)\frac{A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\eta_l\alpha_2\gamma_{c_E}}{\eta_e(1-\alpha_1)+\eta_l(1-\alpha)} \\
& - \frac{(1-\alpha_1)\frac{A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\eta_e\alpha_2\gamma_{c_E}}{\eta_e(1-\alpha_1)+\eta_l(1-\alpha)} \\
& + \frac{(1-\alpha)\frac{A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\gamma\eta_e\eta_l(1-\alpha_1) - (1-\alpha_1)\frac{A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\gamma\eta_e\eta_l(1-\alpha)}{\eta_e(1-\alpha_1)+\eta_l(1-\alpha)} \\
=& \left(\alpha_2 \frac{A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}} - 1\right)\gamma_{c_E} - \frac{A^{1-\epsilon}}{A^{1-\epsilon}+\theta c_E^{\alpha_2(1-\epsilon)}}\alpha_2\gamma_{c_E}\frac{(1-\alpha)\eta_l-(1-\alpha_1)\eta_e}{\eta_e(1-\alpha_1)+\eta_l(1-\alpha)} \\
=& -\gamma_{c_E}.
\end{aligned}$$

ii. As $\gamma_{c_E} > \eta_e\gamma\left(1-\alpha_1\right)/\alpha_2 > \Lambda_{e,EE} < 0$ (see Proposition 3), the efficiency effect is negative. For $\gamma_{c_E} > \eta_e\gamma\left(1-\alpha_1\right)/\alpha_2$, the structural effect is negative (see Proposition 3). Hence, the total effect must be negative.

iii. As $\gamma_{c_E} < \eta_l\gamma\left(1-\alpha\right)/\alpha_2 < \Lambda_{l,EE} > 0$ (see Proposition 2), the efficiency effect is positive. For $\gamma_{c_E} < \eta_l\gamma\left(1-\alpha\right)/\alpha_2$, the structural effect is positve (see Proposition 2). Hence, the total effect must be positive.

□

D. DIRECTION OF TECHNICAL CHANGE WITH INFINITE-DURATION PATENTS

Scientists choose to direct their research at the sector with higher expected firm value (discounted flow of future profits as entrepreneur):

$$E\left[V_{ji}(t=z)\right] = \int_z^\infty E\left[\pi_{ji}(t)\right] exp\left(-\int_z^t \left(1-E\left[s_j(t)\right]\eta_j\right)dt\right)dt \quad \text{with } j\in\{e,l\}.$$

The expected relative value of firm i in sector j at time $t=z$ comprises current (at time z) and discounted future ($t>z$) expected profits ($E\left[\pi_{ji}(t)\right]$). The expected discount rate $(1-E[s_j(t)]\eta_j)$ depends on the expected research effort in sector j at each time t ($E[s_j(t)]$) and the probability of successful research (η_j). Expected relative firm value at $t=z$ is defined as

$$V(t=z) \equiv \frac{E\left[V_{li}(t=z)\right]}{E\left[V_{ei}(t=z)\right]}.$$

Substitutes (i.e. $\epsilon > 1$):
Since equilibrium research allocation depends crucially on the expected discount rate, the subsequent discussion of research equilibria is structured along three discount rate cases (for special cases see 1. & 3., general case 2.):

1. For $(1 - E[s_j(t)]\eta_j) \to 0$, $V(t = z) \to \frac{\Pi_{li}(t=z)}{\Pi_{ei}(t=z)}$, i.e. relative firm value reduces to current relative firm profits. Results of Appendix B can be applied.

2. For $0 < (1 - E[s_j(t)]\eta_j) < 1$ and since $\frac{\partial E[V_{ji}(t=z)]}{\partial \Pi_{ji}(t)} > 0$, $\frac{\partial E[\Pi_{ji}(t)]}{\partial A_j(t)} > 0$, $\frac{\partial E[\Pi_{ji}(t)]}{\partial A_j(t)} > \frac{\partial E[\Pi_{sector \neq j,i}(t)]}{\partial A_j(t)}$, $\lim_{A_j(t)\to 0} E[\Pi_{ji}(t)] = 0$, $\lim_{A_j(t)\to\infty} E[\Pi_{ji}(t)] = \infty$ for each set of parameters there exists a unique relative technology $(A_l(t = z)/A_e(t = z))^*$ such that $\left.\frac{V_{li}(t=z)|_{s(t)=1}}{V_{ei}(t=z)|_{s(t)=0}}\right|_{\frac{A_l(t=z)}{A_e(t=z)}=\left(\frac{A_l(t=z)}{A_e(t=z)}\right)^*} =$ 1. With $\frac{A_l(t=z)}{A_e(t=z)} \overset{(<)}{>} \left(\frac{A_l(t=z)}{A_e(t=z)}\right)^*$, research will take place in the l-sector (e-sector) only. With $\frac{A_l(t=z)}{A_e(t=z)} = \left(\frac{A_l(t=z)}{A_e(t=z)}\right)^*$ there exists a unique equilibrium ($s^{**} \in (0, 1)$) with research directed to both sectors.

   (a) With moderate energy price growth the expected relative profit (and therefore the expected relative firm value ($V(t)$)) increases (decreases) if research is directed to sector l (e) only (Proof: see (B.2)). Therefore a research equilibrium $s^* \in \{0, 1\}$ at time z is always a research equilibrium in $t > z$. An inner equilibrium in $t = z$, $s^*(t = z) = s^{**}$, is an inner equilibrium if and only if $s^*(t) = s^{**}\ \forall\ t \geq z$. With $s^*(t = z) \overset{(<)}{>} s^{**}$ research will take place in sector l (e) for all $t > z$ (follows from (B.2)).

   (b) With strong positive (negative) energy price growth and $\frac{A_l(t=z)}{A_e(t=z)} \overset{(<)}{>} \left(\frac{A_l(t=z)}{A_e(t=z)}\right)^*$ research will occur in sector l (e) at $t = z$ and all $t > z$ (follows from (B.3)). If $\frac{A_l(t=z)}{A_e(t=z)} \overset{(>)}{<} \left(\frac{A_l(t=z)}{A_e(t=z)}\right)^*$ and with strong positive (negative) energy price growth, research will at $t = z$ take place in the e-sector (l-sector) only. Since strong positive (negative) energy price growth increases (decreases) $V(t)$, there exists a time $\tau > z$ where $V(\tau) = 1$ and $V(t > \tau) \overset{(<)}{>} 1$, leading to research equilibrium in sector l (e) for all $t > \tau$ (follows from (B.3)). There are multiple equilibria with $s^*(t = z) \in [0, 1]$ if $\frac{A_l(t=z)}{A_e(t=z)} = \left(\frac{A_l(t=z)}{A_e(t=z)}\right)^*$ and a unique equilibrium with all research in sector l (e) for all $t > z$ in the case of strong positive (negative) energy price growth.

3. For $(1 - E[s_j(t)]\eta_j) \to 1$ and moderate energy price growth, $V(t = z) \to 1$ and there exist two equilibria with all research directed to the e- or the l-sector and multiple equilibria with research directed to both sectors (i.e. $s \in (0, 1)$). With strong positive (negative) energy price growth there exists a unique equilibrium with all research directed to sector l (e), as $\frac{d\Pi_e i(t)}{dt} \to 0$ ($\frac{d\Pi_l i(t)}{dt} \to 0$) and therefore $V(t = z) \overset{(0)}{\to \infty}$.

For discount rates smaller than 1, i.e. $0 \leq (1 - E[s_j(t)]\eta_j) < 1$, from 1. and 2. it follows that alternative patent terms do not induce qualitative differences in the research equilibrium at $t = z$. Research takes place in the relatively more advanced sector; patent terms only affect the level of relative technology threshold $(A_l/A_e)^*$.

In the case of strong positive (negative) energy price growth and $\frac{A_l(t=z)}{A_e(t=z)} \overset{(>)}{<} \left(\frac{A_l(t=z)}{A_e(t=z)}\right)^*$, patent duration affects the timing of the redirection of technical change from the e- to the l-sector (l- to the e-sector). The lower the discount rate the earlier technical change is redirected.

Complements (i.e. $\epsilon < 1$):
With moderate energy price growth, in finite time $V(t) = 1$ holds and s^{**} is the equilibrium research allocation (analogue to moderate energy price growth and complements in AppendixB). With strong positive (negative) energy price growth, in finite time $V(t) \overset{(>)}{<} 1$ holds and $s = 0\,(= 1)$ is the equilibrium research allocation (analogue to strong energy price growth and complements in AppendixB).

Chapter 4

Misconduct and Leader Behaviour in Contests – New Evidence from European Football

Reference for this Paper:

Kempa, Karol and Hannes Rusch (2018), “Misconduct and Leader Behaviour in Contests – New Evidence from European Football”, *MAGKS Joint Discussion Paper Series No. 29-2016*, University of Marburg.

Misconduct and Leader Behaviour in Contests - New Evidence from European Football*

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March 2018

Abstract

This paper provides an empirical investigation of severe misconducts in contests based on data from European football championships. We extend previous studies by differentiating between two types of misconducts both resulting in a yellow card, namely dissents with the referee and other misconducts. Confirming the existing literature, we find that teams with lower ability are more likely to commit sabotage, i.e. fouls, to reduce the opponent's chances for success. Sabotage is also more likely when the outcome of the contests is still open. In addition, we find that dissents with the referee are significantly more likely in the case of an unfavourable score. We introduce a new perspective to the study of football data by distinguishing misconducts of team captains from those of other players. We find that captains engage more in sabotage during important matches and challenge referees' decisions in direct reaction to sanctions awarded to teammates. In contrast to regular players, however, captains do not participate in the escalation of series of retaliative misconducts. Finally, our analyses indicate that all types of misconduct have a negative effect on the likelihood of success.

Keywords: Contest; Dissent; Leadership; Sabotage; Football.

JEL-Codes: D74, D91, M54, Z22.

* We would like to thank Max Albert, Jana Brandt, Laura Druce, Matthias Greiff, Andreas Hildenbrand, Sebastian Krügel, and Jürgen Meckl and for very helpful comments on this paper. Christian Haas provided excellent research assistance. All remaining errors are our own.

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1. Introduction

Contests are situations in which competing individuals or teams exert costly efforts to win prizes. Winning economic contests is of obvious importance in our highly competitive market economy. Therefore, much previous research has tried to identify individual and team-level factors affecting the likelihood of contest success. Most theoretical work on tournaments and contests, e.g., assumes that exerting higher effort than the opponent increases the own probability of winning (see, e.g., Tullock, 1980; Dechenaux et al., 2015).[1] In addition to increasing their own chances to win by exerting more effort, however, contestants often also have a potentially cheaper means at hand: reducing their opponents' chances to win through sabotage (Lazear, 1989). Such destructive behaviour can be observed, e.g., in comparative advertising or political smear campaigns (Chowdhury and Gürtler, 2015).

However, because sabotage is either illegal and/or committed covertly in many economic contests, empirical studies on such destructive behaviour are rather rare. Notable exceptions are studies analysing data from sports contests, most prominently in professional football (soccer), and laboratory experiments with students (Chowdhury and Gürtler, 2015). An advantage of studying behaviour in sports is the observability of the attributes and actions of the competing contestants. In particular, destructive actions against the opponent can be observed openly and rather reliably, allowing for an operationalisation of sabotage as any action that violates the rules of the respective game. Multiple previous studies using football data, e.g., use disciplinary sanctions awarded to players by the referee as measures of sabotage (del Corral et al., 2010; Deutscher and Schneemann, 2017; Deutscher et al., 2013; Garicano and Palacios-Huerta, 2014).

In this paper, we analyse a new dataset on professional football matches. Our analysis adds to the existing literature on misconducts in sports contests as follows. In contrast to previous studies, we differentiate between two types of misconducts that are both sanctioned with a yellow card, namely dissents with the referee and other misconducts. According to FIFA's official *Laws of the Game*, a player is to be cautioned and shown a yellow card for any dissent by word or action against the referee. The important point is that dissent targets the referee, while other cautioned misconducts, such as severe and repeated fouls or delaying the restart of play, are aimed at opponent players, i.e. the opposing team. As only the latter is sabotage as defined by contest theories, our differentiation allows for a more precise empirical analysis of sabotage in sports contests.

Complementarily, the differentiation we introduce allows for a distinct analysis of dissents against the authority in charge of the interpretation and enforcement of the contest's rules, i.e. the referee. Thus, in addition to sabotage, we are able to study a second route which contestants might take towards influencing the outcome of a contest: trying to influence how the rules of the game are implemented.

Further, we add a new perspective to the literature by explicitly distinguishing between the

[1] In the case of great heterogeneity of players, the theoretical research on contests has shown that weaker players may be discouraged from exerting effort (Dechenaux et al., 2015).

behaviour of team captains and other players. According to previous survey-based studies, team captains are typically older and more experienced team members taking on leadership tasks, such as on-field motivation and encouragement, and seem to have specific skills, such as remaining positive and controlling their emotions (Dupuis et al., 2006; Elgar, 2016; Fransen et al., 2014). By incorporating this second distinction, we are able to investigate whether players in a leadership role within a team in competition make different use of dissent and sabotage than regular players.

Our main results are that, in line with previous findings, destructive actions against the opponent increase with lower team ability. However, dissents with the referee are not affected by ability. Rather, the current state of the match, e.g. an unfavourable goal difference, increases the occurrence of dissent. Differentiating between player types shows that captains, in contrast to other players, do not seem to participate in the escalation of series of retaliative misconducts. Furthermore, captains are more likely to protest and to use sabotage during important matches. In addition, they are more likely to challenge referees' decisions in direct reaction to sanctions awarded to their teammates. Finally, we analyse the impact of misconducts on match outcome and find that this kind of sabotage likely reduces a team's chances of success.

The paper is organised as follows. Section 2 provides a brief overview of previous literature. In Section 3 the dataset and its variables are introduced. Section 4 presents our econometric analysis. Section 5 discusses the results and Section 6 concludes.

2. Overview of Previous Literature

Sabotage in contests has been investigated in numerous experimental studies (see, e.g., Carpenter et al., 2010; Harbring and Irlenbusch, 2011; for reviews see Chowdhury and Gürtler, 2015; Dechenaux et al., 2015). However, studies on sabotage outside the lab are rare. One obvious reason is that sabotage is usually associated with disreputable and/or illegal activities. Hence, individuals engaging in sabotage try to conceal such actions, rendering them difficult to observe in the field (Balafoutas et al., 2012).

The main body of observational research on sabotage in contests uses sports data (Chowdhury and Gürtler, 2015). An exception are, e.g., Jirjahn and Kraft (2007), who use intra-firm wage dispersion data and hence face smaller challenges in generalising their results to labour market contexts. A disadvantage of such analyses, however, is their very indirect measurement of sabotage. Jirjahn and Kraft (2007), e.g., find effects of wage-dispersion and promotions on employees' efforts and then argue that sabotage caused the outcome they observe. A main advantage of data from sports tournaments is that destructive actions against the opponent athlete or team aiming to reduce the opponent's chances to win can be observed directly and quite reliably.

Balafoutas et al. (2012) analyse the effect of contestants' relative skill levels on sabotage as well as the cost of engaging in such in Judo world championships. As a measure of sabotage, the authors use *shido*, a sanctioning mechanism against mild violations of the spirit of Judo.

Their results show that contestants with lower ability use sabotage more often than contestants with greater ability. Furthermore, Balafoutas et al. (2012) examine the effect of a rule change in Judo introduced in 2009. Prior the rule change, every shido was penalised with one point for the opponent. After the rule change, the first *shido* merely results in a caution, but subsequent *shidos* still increase the opponent's score. Using this rule change as a natural experiment, the authors show that sabotage significantly increased after the rule change that decreased the cost of sabotage.

Garicano and Palacios-Huerta (2014) and del Corral et al. (2010) study a similar natural experiment. They analyse the effect of changing the reward for winning a football match from two to three points. Using match-level data, Garicano and Palacios-Huerta (2014) find that the increase in prize spread, i.e. the difference between the prize received by the winner and the loser of a contest, led to significantly more sabotage compared to the period before the rule change. Similarly, del Corral et al. (2010) examine the change in the probability of red cards being awarded after the increase in prize spread. Controlling for within-match dynamics, such as the minute of the match and the goal score, they find an increased probability for sabotage in teams that are in a losing position.

Frick et al. (2008) analyse how sabotage is affected by the difference in ability of two competing teams, determined based on betting odds prior to the respective match. They find that sabotage, measured as the number of yellow and red cards, increases when teams of similar ability compete. Using data from football and basketball, Stulp et al. (2012) find similar results. Measuring differences in ability as the absolute difference in table ranks for football and as the share of won games per season in the case of basketball, they find that the smaller the difference in the ability of two teams, the higher the number of fouls per match (basketball and football) and the more yellow cards are given per match (football).

Deutscher et al. (2013) explicitly differentiate between effort compliant with the rules of the game (fair tackles) and sabotage (fouls) in football matches. Their results indicate that weak contestants engage more in sabotage, while contestants with greater abilities exert more compliant effort. Deutscher and Schneemann (2017) further refine this analysis by using information on the ex-ante heterogeneity of competing football teams, based on betting odds, and within-game information, namely the goal difference. Like del Corral et al. (2010), the authors control for within-game dynamics and show that both a lower ex-ante ability as well as a negative goal difference increase sabotage (measured as severe misconduct penalised by a yellow card).

Previous research on leadership in sports has mainly concentrated on coaches. However, team members can also take on leadership roles (Loughead et al., 2006). In the present study, we focus on formally appointed or elected leaders, namely team captains.[2] Team leaders typically are more experienced team members taking on tasks such as on-field team motivation (Fransen et al., 2014). Also, as Elgar (2016) show using data from the London 2012 Olympics and Par-

[2]Captains typically are the peer leaders within teams, although other team members might simultaneously take on specific leadership roles.

alympics, team captains are often considerably older than their teammates and their influence on team discipline increases with age. Psychological research on captains has found them to have specific skills such as remaining positive and controlling their emotions (Dupuis et al., 2006). In their study on adolescent football players, Price and Weiss (2011) found that peer leaders are characterised by higher peer acceptance, behavioural conduct, and intrinsic motivation. However, the specific role team leaders play in contests has become a focus of theoretical and empirical interest in economics only very recently (Eisenkopf, 2014; Gauriot and Page, 2015). As previous evidence on team captains' characteristics is largely based on interviews and surveys of athletes, it seems worthwhile to investigate whether differences between team captains and other players in sports contests can be observed in our behavioural data as well.

3. Empirical Framework

3.1. Data

For our analysis, we use data from live tickers that provide (almost) real-time coverage of an event, in our case football matches.[3] We used data from the German football portal *weltfussball.de*, which covers football games of many European football leagues by live tickers and usually contains information on the causes of yellow cards in the respective posts. The advantage of this portal compared to most of its alternatives is that ticker texts remain online after the match. League games with dissents were identified by searching the texts of the available live tickers for yellow cards and German terms for *dissent*.[4] This procedure resulted in a dataset containing 227 matches in 10 European football leagues from the seasons 2004/2005 to 2013/2014. The dataset includes 1,345 yellow cards. Whenever the cause of at least one caution was not identifiable, the websites *kicker.de*, *transfermarkt.de*, and *fussballoesterreich.at* were used to identify the missing reason(s) and to cross-check the data. Furthermore, these sources were used to identify the captains of the respective teams in all matches.

In contrast to previous studies using football data, our dataset is not a balanced panel covering only one league over one or several seasons. Both del Corral et al. (2010) and Garicano and Palacios-Huerta (2014) use data on all matches from two seasons of the Spanish First Division (*Primera División*, while Deutscher et al. (2013) as well as Deutscher and Schneemann (2017) use data from the first division in Germany (*Bundesliga*) covering three seasons. In our dataset, the distribution of matches across the 10 European leagues is very unbalanced (see Table 5 in the Appendix). As the data is drawn from a German website, leagues in German speaking countries, i.e. Austria and Germany, are overrepresented. Hence, there is a possibility that our

[3]Live tickers are usually offered by online news/sports media. The tickers consist of stenotype short comments in varying degrees of frequency (also based on the type of broadcasted sport) with information on decisive game events as well as important plays. In individual cases, live tickers are enriched with statistical materials (lineups, player data, etc.).

[4]These terms are "meckern", "protestieren", and "beschweren"; typical German expressions for protesting in football.

data gathering process introduced biases. We address this potential issue by providing a replication of previous results in our new dataset prior to presenting our main original results. As we will show below, we replicate all core findings of previous empirical studies which applied a similar methodology. Thus, although our dataset contains fewer observations and a larger and less balanced distribution of matches across leagues than those used in previous studies, we are confident that it does not differ from previously used data in the relevant respects. In fact, our contribution complements previous studies, because it contains data from divisions below the first league and covers countries not studied before.

3.2. Methodology and Variables

In our analysis, we use the minute of the match as the unit of observation, which is a relatively new approach in the analysis of football matches (Buraimo et al., 2010; Buraimo et al., 2012; del Corral et al., 2010). In contrast to analyses based on matches as the unit if observation, e.g. Frick et al. (2008) and Stulp et al. (2012), this approach allows for capturing within-game dynamics in detail, because the order of all events of interest occurring throughout the game is included in the analysis. Our binominal dependent variable takes the value 1 when a yellow card (of specific type) is awarded to a player of a given team in the respective minute and 0 otherwise. In contrast to previous studies that analysed all yellow cards jointly, we extend the analysis of illegal behaviour in contests in two directions. First, we differentiate between dissents and other misconducts. Second, we separately analyse the cautioned illegal behaviour of captains and of other players. Descriptive statistics are reported in Table 1.

For the analysis we use the following set of independent variables. The variable *goal difference* measures the current difference in goals from the respective team's perspective. It is expected that teams lagging behind in score increase their effort and that this leads to an increase in illegal activities, hence to an increased propensity of receiving yellow cards (Buraimo et al., 2010; Deutscher and Schneemann, 2017). However, it is also possible that with high goal differences, i.e. when a match is almost certainly decided, players' efforts and hence the likelihood of yellow cards decrease. In order to capture these potentially non-linear effects of the goal difference on players' behaviour and on awards of yellow cards, we introduce the control *goal difference squared*.

The variable *minute* captures the minute of the regular playing time. For all events that occurred in the stoppage time of the first and the second half of a match, *minute* takes the values 45 and 90, respectively. Hence, the 45th and 90th minute are 'longer' minutes compared to the other minutes in the dataset. Although the exact minutes in the respective stoppage time are available in the dataset, it is problematic to use this information in this analysis. If a yellow card is given in the first minute of stoppage time at the end of the first half, *minute* would take the value 46. The value would be the same for events in the first minute of the second half, although the situation is considerably different. Hence, *minute* contains only the minutes of the regular game time. Following Buraimo et al. (2010) and Buraimo et al. (2012), the information

Table 1: Descriptive statistics differentiated by captains and other players and dissents and other misconducts

	Captain		Other Player		Dissent		Other Misconduct	
	mean	sd	mean	sd	mean	sd	mean	sd
Minute	58.70	22.67	56.57	24.11	59.71	22.86	55.90	24.23
Minute squared	3955.62	2507.78	3781.17	2604.71	4085.76	2571.15	3711.20	2596.51
45th Minute	0.01	0.12	0.01	0.08	0.01	0.10	0.01	0.08
90th Minute	0.06	0.23	0.05	0.22	0.07	0.25	0.05	0.21
Yellow cards last 3 min	0.15	0.38	0.12	0.35	0.17	0.39	0.11	0.34
Opponent yellow cards last 3 min	0.14	0.35	0.15	0.38	0.13	0.34	0.16	0.39
Yellow cards prior	1.29	1.34	1.23	1.26	1.31	1.27	1.21	1.27
Opponent yellow cards prior	1.52	1.45	1.33	1.30	1.34	1.30	1.36	1.32
Goal difference	-0.25	1.15	-0.14	1.12	-0.47	1.15	-0.06	1.10
Goal difference squared	1.37	2.13	1.28	2.18	1.54	2.68	1.21	1.99
Difference in bookmaker probability	-0.01	0.32	-0.04	0.34	-0.01	0.35	-0.05	0.33
Difference in bookmaker probability squared	0.10	0.15	0.12	0.15	0.12	0.17	0.11	0.15
Competitiveness	0.38	0.49	0.56	0.99	0.55	0.92	0.54	0.96
Attendance	9.55	1.30	9.48	1.28	9.46	1.27	9.49	1.29
Derby	0.09	0.29	0.09	0.29	0.09	0.28	0.10	0.30
Observations	139		1206		316		1029	

on minutes in stoppage time is captured by two dummy variables, *45th minute* and *90th minute*, where *45th minute* takes the value 1 whenever a yellow card was given in the stoppage time of the first half while *90th minute* is 1 for all yellow cards in the stoppage time of the second half.

The variables *yellow cards prior* and *opponent yellow cards* prior were included in order to control for the potential effects of previous cautions on players' misconducts. The former gives the number of yellow cards a team has received before the respective caution, whereas the latter measures the number of yellow cards the opponent team has received. As proposed by Buraimo et al. (2010), the variables *yellow cards last 3 min* and *opponent yellow cards last 3 min* are also included to capture potential dynamics in players' direct reactions to previous cautions. They contain the number of cautions received by the team of the cautioned player and the opposing team, respectively, within the last 3 minutes before an event and are separated from the number of yellow cards received prior to this time horizon. The direction of a potential effect of previous sanctions on dissents and sabotage is not clear. With respect to the incentive to protest against the referee, the number of previously received yellow cards might increase the probability of dissent by players of this team. A large number of cards could be perceived by players as unfair treatment by the referee and hence cause them to challenge his decisions.

However, a high number of previous yellow cards might also be a consequence of an escalation of illegal contest behaviour between the competing teams and hence increase the likelihood of further sabotage against the opposing team. Yet, at the same time, numerous previous cautions for both the own and the opposing team might increase the perceived risk of punishment, which could deter further misconducts.

To control for difference in team quality, we use the difference in the winning probabilities of both teams. We calculate the *difference in bookmaker probability* from betting odds available on the website *betexplorer.de*, which provides a comprehensive data base of historical betting odds covering all leagues and seasons in our dataset. The higher the *difference in bookmaker probability*, the higher is a team's ability relative to its opponent. Betting odds have been used frequently in previous studies as a measure of relative team strength and have proven to be a good predictor of the match outcome (Buraimo et al., 2010; Forrest et al., 2005). A particular advantage of this measure is that it does not only consider the respective teams' latest results, but also other relevant and recent information, such as injuries and fitness of (key) players, dismissals of coaches, etc. Similar to goal difference, the variable's square, *difference in bookmaker probability squared*, is included to account for potential non-linearities (Buraimo et al., 2012).

We also include a variable to account for the competitiveness of the respective match. Similar to Witt (2005), we calculate the variable *competitiveness* as the absolute difference in table positions of the competing teams prior to the match of interest weighted by the number of remaining matches in the season. Note that the smaller the value of *competitiveness*, the higher the importance of the match. The advantage of this measure, compared to relying on the difference in table positions, is that it accounts for the fact that matches against neighbouring teams in the table gain importance towards the end of the season.[5]

Another factor that might affect the behaviour of contestants is the atmosphere in the stadium (Deutscher and Schneemann, 2017). Hence, we include the log of the number of spectators at the respective match into our models (*attendance*).

Furthermore, strong rivalries among teams might increase the intensity of aggressive behaviour in the respective matches. Following Buraimo et al. (2012), we control for this potential effect by including the variable *derby* that takes the value of 1 if both teams are either local rivals (e.g. Manchester City and Manchester United) or harbour historical rivalries (e.g. FC Barcelona and Real Madrid) and 0 otherwise.

Finally, as previous evidence shows that referees on average award more yellow cards to away teams, i.e. are home biased (see, e.g., Dohmen, 2008; Page and Page, 2010), we include the dummy variable *away* taking the value of 1 if the team under consideration is the away team and 0 for the home team.

[5] In many European football leagues, disbursements from TV rights to the clubs are increasing with a better table position in the previous season. Furthermore, finishing on one of the first table positions might lead to qualification for European competitions (in case of first divisions) or promotions to a higher league (in case of lower divisions). Teams in the lowest positions in the table get relegated to a lower league.

4. Results

For our analysis we combine the method of Deutscher and Schneemann (2017) with the minute-by-minute approach (Buraimo et al., 2010; Buraimo et al., 2012; del Corral et al., 2010). As the latter three studies investigate referee bias, they separately model the probability of cards awarded to the home team and cards the away team using a bivariate probit model framework. Following Deutscher and Schneemann (2017), who also investigate misconducts in a within-match framework, we estimate the probability of receiving a yellow card (of respective type) jointly for home and away teams. As the respective dependent variables are bivariate, we use probit models to estimate this probability. As Buraimo et al. (2010) and Deutscher and Schneemann (2017), we cluster the data by match to account for dependencies of observations within matches. To capture fixed effects of seasons and the different leagues, two respective sets of dummy variables are included in all specifications. Prior to presenting our main analyses, we provide estimation results based on all yellow cards, i.e. not distinguishing between protests and fouls, and compare these to those of previous studies. We then estimate two models to analyse the drivers of dissenting behaviour and other misconducts. Subsequently, we distinguish between the behaviour of team captains and other players. Our analysis of the impact of misconducts on the likelihood of winning a match concludes this section.

4.1. Replication of previous findings

In this subsection we jointly analyse all yellow cards. The following results provide a validation of our new dataset and add to the previous literature by replicating its main results using new data from across various European leagues including lower divisions. The results of our probit model for all yellow cards are displayed in Table 3 (Model 0).

We find significant negative effects of both *goal difference* and *goal difference squared*. The negative coefficient of goal difference implies that the probability of a yellow card of any kind increases in the case of an unfavourable score from the perspective of the offending player's team. The result for *goal difference squared* indicates that the probability of yellow cards decreases the more a team is leading or lagging behind, i.e. there is an inverted U-shaped relationship between *goal difference* and the likelihood of a yellow card. Both results are in line with the findings of Buraimo et al. (2010), whereas in Buraimo et al. (2012) only the squared term is significant. Deutscher and Schneemann (2017) and del Corral et al. (2010) do not consider a squared term, but also find a significant negative effect of the match score.

The positive and significant coefficient of *minute* and the negative coefficient of *minute squared* indicate that the probability of severe misconduct increases in the course of a match, however, at a decreasing rate, which is similar to the findings of Buraimo et al. (2010), Buraimo et al. (2012), del Corral et al. (2010), and Deutscher and Schneemann (2017). The dummy variables *45th minute* and *90th minute* are both positive and significant, as found by Buraimo et al. (2010) and del Corral et al. (2010). Buraimo et al. (2012) find significant negative effects of

Table 2: Probit Regressions with yellow card awarded for dissent, other misconduct, and all yellow cards as dependent variables

	(0) All		(1) Dissent		(2) Other Misconduct	
Goal difference	-0.0625***	(4.98)	-0.1488***	(5.06)	-0.0246*	(1.86)
Goal difference squared	-0.0179***	(2.82)	-0.0193	(1.50)	-0.0193***	(2.59)
Minute	0.0173***	(8.37)	0.0190***	(4.54)	0.0153***	(7.04)
Minute squared	-0.0001***	(3.58)	-0.0001*	(1.95)	-0.0001***	(3.09)
45th Minute	1.8595***	(31.18)	1.5099***	(4.35)	1.5199***	(6.87)
90th Minute	1.3106***	(18.92)	1.0369***	(6.83)	1.1275***	(12.77)
Yellow cards last 3 min	-0.0173	(0.44)	0.0992*	(1.85)	-0.0652	(1.47)
Opponent yellow cards last 3 min	0.1489***	(4.61)	0.0325	(0.50)	0.1699***	(4.76)
Yellow cards prior	-0.1042***	(7.55)	-0.0917***	(4.07)	-0.0960***	(6.30)
Opponent yellow cards prior	0.0005	(0.03)	-0.0342*	(1.67)	0.0134	(0.89)
Difference in bookmaker probability	-0.1429***	(3.52)	0.0872	(1.34)	-0.2102***	(4.83)
Difference in bookmaker probability squared	-0.1208	(0.97)	-0.0726	(0.61)	-0.1275	(0.96)
Competitiveness	-0.0098	(0.99)	-0.0053	(0.52)	-0.0101	(0.97)
Attendance	0.0041	(0.16)	0.0218	(1.00)	-0.0010	(0.03)
Derby	0.0728	(1.36)	-0.0002	(0.00)	0.0845	(1.41)
Away	0.0398	(1.52)	0.0892**	(2.00)	0.0186	(0.66)
Constant	-2.5464***	(10.43)	-3.3617***	(15.08)	-2.5337***	(9.21)
Observations	41088		41088		41088	
Pseudo R^2	0.054		0.070		0.044	

Notes: Absolute t-statistics in parentheses. Standard errors are clustered at the match level to account for within-match dependences of observations. Significance: * p<0.10, ** p<0.05, *** p<0.01.

both dummies for the Spanish First Division. For matches in the UEFA Champions League, they find a significant positive effect of *45th minute* and an insignificant effect of *90th minute*.

We included the four controls *yellow cards prior*, *opponent yellow cards prior*, *yellow cards last 3 min*, and *opponent yellow cards last 3 min* as proposed by Buraimo et al. (2010) and Buraimo et al. (2012). In line with both studies and Deutscher and Schneemann (2017), we find that the number of yellow cards a team has received previously (except the last 3 minutes), yellow cards prior, negatively affects the likelihood of a yellow card. Furthermore, the positive effect of opponent yellow cards last 3 min we find is in line with Buraimo et al. (2010) and Buraimo et al. (2012). The other two control variables have the same sign as in these two studies, but are not significant in our model. However, in one specification in Buraimo et al. (2012) as well as in Deutscher and Schneemann (2017) the effect of the number opponent yellow cards prior is also not significant.

In line with previous findings, we find that difference in bookmaker probability has a significant and negative effect on the probability of a yellow card (Buraimo et al., 2010, 2012; Deutscher and Schneemann, 2017). The effect of attendance is not significant in our study like in del Corral et al. (2010), Deutscher and Schneemann (2017), Witt (2005). Finally, derby has no effect on the probability of any type of cautioned misbehaviour, which supports the results of Buraimo et al. (2010) for the German *Bundesliga* and Buraimo et al. (2012) for the Spanish *Primera División*.

Thus, by and large, we replicate the main results of relevant previous studies. Therefore, we consider our new dataset validated. In the remainder of this section, we present our main original results.

4.2. Dissents vs. Other Misconducts

In order to differentiate between dissents and other misconducts, we estimate two models. The dependent variable in Model 1 only contains yellow cards awarded for dissents, whereas Model 2 covers the remaining yellow cards.

The negative coefficients of *goal difference* in Models 1 and 2 imply that the probability of both dissents against the referee and misconducts aimed at the opponent increase as the goal difference decreases. Players in teams lagging behind are more likely to protest against referee decisions as well as to engage in severe foul play. In the latter case, however, the coefficient is only significant at the 10%-level. While the coefficient of *goal difference squared* is not statistically significant for dissents, it is significant (at the 1%-level) and negative for other misconducts.

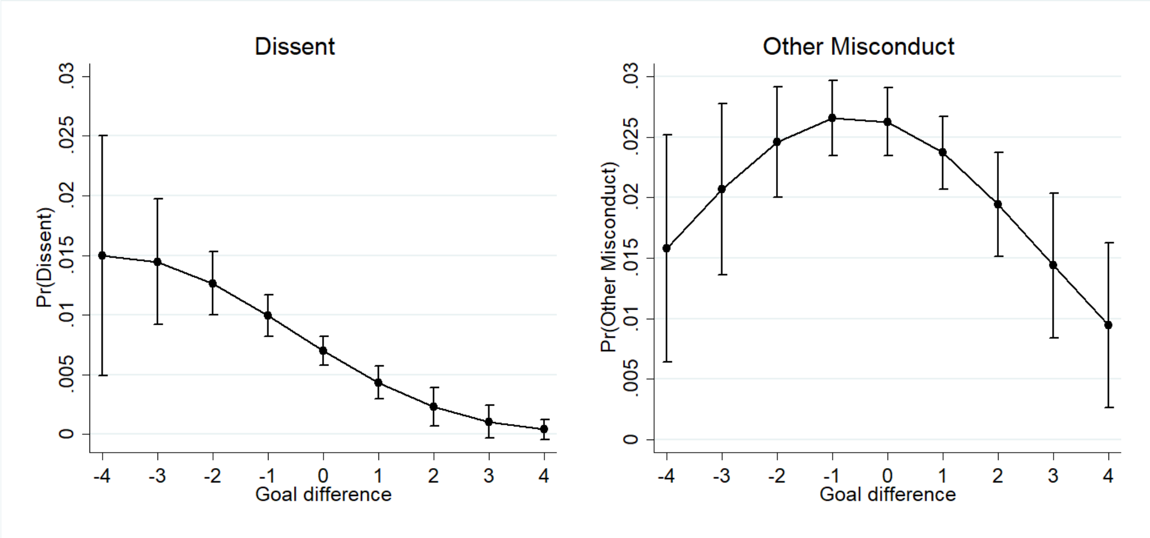
The differences between the effects of the current score on dissent and other misconducts are depicted in Figure 1. The figure shows the probability of dissent (per minute) as well as the probability of other misconduct (per minute) for different goal differences as predicted by Models 1 and 2, respectively. For other misconducts, there is an obvious inverted U-shaped relationship as indicated by the coefficients. As long as the match is tight, i.e. the absolute goal difference is small, the probability of sabotage is high.

For dissents against the referee, however, the effect of *goal difference* is substantially different. As can be seen in Figure 1, the probability of protesting against the referee increases, when the goal difference decreases. In teams leading by a large margin, almost no dissents with the referee can be observed, while protesting against the referee becomes substantially more frequent when the team is lagging behind.

Another essential difference between dissents and other misconducts is the effect of the difference in teams' abilities. According to Model 2, *difference in bookmaker probability* has a significant and negative effect on the probability of a severe foul. The more inferior a team is with respect to its ability compared to the opponent, the more sabotage is used to compensate this disadvantage. In contrast, *difference in bookmaker probability* does not affect dissenting behaviour of contestants.

The effects of the difference in ability on dissent and misconduct aimed at the opponent are

Figure 1: Adjusted predictions of Dissent (left) and Other Misconduct (right) per minute at different goal differences and the means of other covariates with 95% confidence intervals.



illustrated in Figure 2. For the latter, we find a relationship as predicted by theories on sabotage in contests: the lower the ability of a team compared to its opponent, the higher the probability to engage in sabotage (Lazear, 1989). For dissents, the probability is almost identical across different values of *difference in bookmaker probability*. The difference in the abilities of the contestants does not significantly affect the probability to protest against the referee's decision.

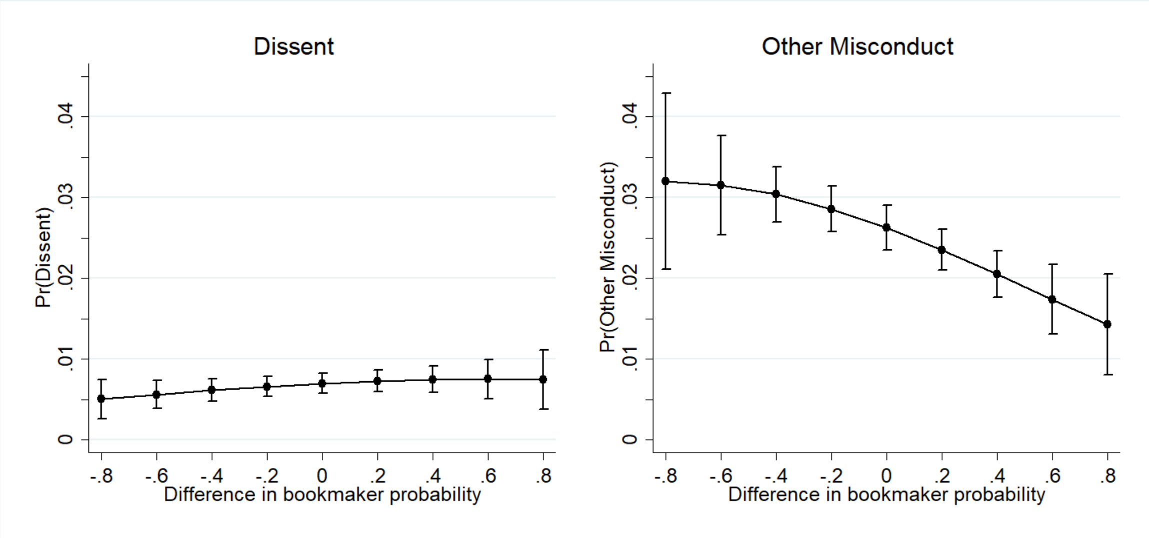
Further noteworthy differences between dissents and other misconducts include the following. Previous sanctions have a differentiated effect. In Models 1 and 2, the number of yellow cards a team received prior to the last three minutes of the subject minute reduces the probability of both dissents and severe fouls. However, while the number of prior cards the opponent team received does not affect other misconducts, it affects the likelihood of dissents negatively.

Dissents and foul plays are reversely affected by yellow cards that the competing teams were awarded recently. In the case of dissents, the coefficient of *yellow cards last 3 min* is positive and weakly significant. This indicates that immediately after a cautioned sabotage of a player from the own team, there is an increased probability for protesting behaviour. In contrast, the number of yellow cards the opponent team received in the last three minutes (*opponent yellow cards last 3 min*) does not affect dissents. With respect to other misconducts, the results are reversed. While recently received yellow cards by the own team are statistically insignificant, the number of yellow cards the opponent received in the last three minutes positively affects the likelihood of other misconducts. Finally, for away teams, we only find an increased probability for dissents, but not for other misconducts.

4.3. Captains vs. Other Players

We now analyse the behaviour of captains and other players by further disaggregating the dependent variables. We divide yellow cards for dissents into dissents of captains and dissents

Figure 2: Adjusted predictions of Dissent (left) and Other Misconduct (right) per minute at different levels of the difference in ability and the means of other covariates with 95% Confidence Intervals.



of other players. Cautions for misconducts aimed at the opponent are similarly divided. The independent variables remain the same as above. Table 3 summarises the results.

Most of the pre-match and within-match covariates have qualitatively the same effects on sabotage behaviour of captains and regular players. There are, however, some notable differences between the two player types. Regular players' sabotage behaviour is affected by the number of yellow cards the opponent team has received in the last three minutes prior to the subject minute (positive and significant coefficient of *opponent yellow cards last 3 min*). If the opponent just engaged in severe foul play, players of the fouled team are more likely to engage in sabotage themselves, which indicates retaliative foul play. Team captains, however, do not participate in such retaliatory escalations of misconducts during the match. The number of yellow cards recently awarded to the own team (*yellow cards last 3 min*) increases captains' propensity to dissent, while it has no effect on the dissenting behaviour of other players.

Finally, only team captains' behaviours seem to be affected by the competiveness of the match, i.e. the absolute difference in the table rank of competing teams relative to the remaining matches in the season (negative and significant coefficients of *competitiveness* in Models 3 and 5). The more important a match is, the higher is the likelihood of misconducts by captains.

Table 3: Probit Regressions with yellow cards for dissents and yellow vards for other misconducts awarded to captains and other players, respectively, as dependent variables

	Dissent		Other Misconduct	
	(3)	(4)	(5)	(6)
	Captain	Player	Captain	Player
Goal difference	-0.1311**	-0.1447***	-0.0433	-0.0213
	(2.16)	(5.26)	(1.39)	(1.52)
Goal difference squared	-0.0198	-0.0186	-0.0111	-0.0194**
	(0.69)	(1.57)	(0.79)	(2.50)
Minute	0.0345***	0.0152***	0.0096*	0.0153***
	(3.61)	(3.49)	(1.66)	(6.95)
Minute squared	-0.0002***	-0.0000	-0.0000	-0.0001***
	(2.60)	(1.10)	(0.57)	(3.11)
45th Minute	0.0000	1.5797***	1.6422***	1.2186***
	(.)	(4.49)	(4.90)	(4.67)
90th Minute	0.9629***	0.9641***	0.6933**	1.1038***
	(3.66)	(6.44)	(2.57)	(12.05)
Yellow cards last 3 min	0.1851**	0.0623	-0.1241	-0.0563
	(2.00)	(1.05)	(1.08)	(1.23)
Opponent yellow cards last 3 min	-0.0360	0.0412	0.1233	0.1671***
	(0.27)	(0.62)	(1.31)	(4.48)
Yellow cards prior	-0.0810*	-0.0879***	-0.0864**	-0.0924***
	(1.65)	(3.83)	(2.07)	(5.99)
Opponent yellow cards prior	-0.0421	-0.0294	0.0632*	0.0054
	(0.91)	(1.35)	(1.91)	(0.36)
Difference in bookmaker probability	0.0643	0.0883	-0.0902	-0.2128***
	(0.48)	(1.26)	(0.70)	(4.82)
Difference in bookmaker probability squared	-0.4656	0.0313	-0.3814	-0.0909
	(1.26)	(0.29)	(1.41)	(0.66)
Competitiveness	-0.1130*	0.0064	-0.0749*	-0.0047
	(1.67)	(0.60)	(1.79)	(0.43)
Attendance	0.0435	0.0143	0.1099*	-0.0129
	(0.62)	(0.55)	(1.75)	(0.43)
Derby	-0.2337	0.0481	0.0439	0.0838
	(1.09)	(0.73)	(0.43)	(1.31)
Away	0.0703	0.0882*	-0.0439	0.0252
	(0.76)	(1.85)	(0.57)	(0.86)
Constant	-4.4540***	-3.2761***	-4.4834***	-2.4383***
	(6.53)	(12.98)	(7.10)	(8.55)
Observations	41070	41088	40360	41088
Pseudo R^2	0.087	0.065	0.061	0.042

Notes: Absolute *t*-statistics in parentheses. Standard errors are clustered at the match level to account for within-match dependences of observations. Significance: * p<0.10, ** p<0.05, *** p<0.01. The variable 45th Minute is omitted in Model (3) as there were no yellow cards awarded for dissent to captains in the stoppage time of the first half in our dataset.

4.4. Impact of Sabotage and Dissents on Team Success

We now turn to the analysis of the impact of dissents and sabotage on teams' outcomes. For the dependent variable, the match-level success of a team, two alternative measures are used. *Final score* is measured as the goal difference between a team and its opponent at the end of the match. Alternatively, the *match outcome* – loss, draw, win – is used as dependent variable. Both measures have been used in similar previous studies (Anders and Rotthoff, 2011; Deutscher and Schneemann, 2017; Franck and Nüesch, 2010).[6] As measures for the intensity of dissents and sabotage behaviour of a team in a match, we use the difference between dissents and other misconducts of the respective team and its opponent. To control for the relative ability of both teams, which is an important determinant of the outcome of a match, we include *difference in bookmaker probability*. We further include *attendance*, *derby*, and length of the stoppage time (*minutes stoppage time*) as controls.

Table 4 contains the results of OLS regressions for the models with final score as dependent variable and ordered probit regressions for the case of match result. When considering the difference in all yellow cards that the teams received (Models 7 and 8), the estimation results show that the intensity of a team's illegal behaviour negatively affects that team's outcome, while such illegal behaviour by the opponent team positively affects chances for success (negative coefficient of *difference in all yellow cards*). These findings are in line with Deutscher and Schneemann (2017), who use a very similar model specification with data from the German *Bundesliga*. Furthermore, there seem to be no qualitative differences between the effects of dissents and other misconducts, when these are considered separately (Models 9 and 10).

We repeated the analyses as presented above with controls for the actual performance of both contestants in the match by including the number of shots on target by both teams.[7] The results of these regressions are shown in Table 6 in the Appendix. Even after including these controls, we still find indications of detrimental effects of misconducts on team success. Hence, there seems to be either a negative or no impact of illegal team behaviour on team outcome, irrespective of whether it takes the form of dissents or other misconducts. This finding is in line with previous results (Anders and Rotthoff, 2011; Carmichael and Thomas, 2005; Carmichael et al., 2000; Deutscher and Schneemann, 2017).

5. Discussion

Our differentiation between sabotage aimed at the opponent and dissent against the referee provides valuable new insights. For misconducts aimed at the opposing team directly, i.e. fouls, we find that contestants with lower ability engage more in sabotage, which is in line with previous

[6] As two teams compete in a match, the match result – goal difference or match outcome – can be expressed from both teams' perspectives. We expressed all variables from the perspective of the home team. This, however, does not affect our analysis as expression the variable from the away team's perspective would yield symmetric results.

[7] The data for shots on target and opponent team shots on target were obtained from *football-data.co.uk*, *sport1.de*, and *bundesliga.at*.

Table 4: OLS Regressions with final score (goal difference at the end of the match) and ordered probit regressions with match result (loss, draw, win) as dependent variables

	(7) Final Score	(8) Match Result	(9) Final Score	(10) Match Result
Difference in bookmaker probability	1.6037***	1.3441***	1.7382***	1.4754***
	(4.89)	(4.65)	(5.26)	(4.97)
Attendance	-0.1562	-0.1841	-0.1522	-0.1738
	(0.97)	(1.29)	(0.95)	(1.21)
Derby	0.4189	0.5309	0.3072	0.4422
	(1.35)	(1.48)	(1.05)	(1.24)
Minutes stoppage time	-0.0979	-0.0393	-0.1129*	-0.0440
	(1.51)	(0.67)	(1.85)	(0.76)
Difference in all yellow cards	-0.2189***	-0.2058***		
	(4.54)	(4.78)		
Difference in dissents			-0.4284***	-0.3973***
			(5.53)	(5.08)
Difference in other misconducts			-0.1105*	-0.1139**
			(1.85)	(2.38)
Observations	227	227	227	227
R^2	0.285		0.322	
Pseudo R^2		0.157		0.180

Notes: Absolute t-statistics (OLS) and z-statistics (ordered probit) in parentheses. Robust standard errors. Significance: * p<0.10, ** p<0.05, *** p<0.01.

findings (Balafoutas et al., 2012; Deutscher and Schneemann, 2017; Deutscher et al., 2013). In contrast, the likelihood of misconducts aimed at the contest's referee, i.e. dissents, seems to be independent of ability. As only the former is sabotage as defined by contest theories, we provide a more precise analysis of sabotage in contest compared to previous studies. Further, we find that the marginal effect of difference in bookmaker probability on the probability of sabotage is stronger than its effect on the probability of any misconduct.[8] These results show that estimates based on all sanctioned misconducts, as Deutscher et al. (2013), Deutscher and Schneemann (2017), and our Model 0, are driven by foul plays and underestimate the effect of ability on the likelihood of sabotage.

Further, we find an inverted U-shaped relationship between *goal difference* and sabotage. An explanation lending itself is that a realistic chance to improve the outcome of the match provides incentives to exert effort, both 'positive' effort aimed at increasing the own team's productivity as well as 'negative' effort, i.e. sabotage. When the match is mostly decided, however, sabotage is reduced, because players have lower incentives to engage in costly sabotage if the expected pay-off decreases. This result could be partly driven by referee behaviour. The observation of more frequent misconducts, e.g. in close matches, might induce stricter refereeing. This could, to a certain extent, further increase the number of yellow cards for any type of misconduct in tight matches. The effect of player behaviour, however, seems to be stronger as such an increase

[8]The marginal effect of *difference in bookmaker probability* on the probability of sabotage per minute is -.011 (Model 2), while its marginal effect on the probability of any misconduct per minute is -.009 (Model 0).

in sanctions in close matches cannot be observed for dissents.

Our finding that the likelihood of dissents against the referee increases in the case of an unfavourable score could indicate self-serving (or team-serving) attribution as, e.g., predicted by the attributional theory of motivation and emotion (Weiner, 1985, 1986; for a review, see Allen et al., 2012). One main prediction of this theory is that individuals attribute success to internal factors, e.g. abilities, and failure to external factors, e.g. bad refereeing (Rees et al., 2005). Lau and Russell (1980) provide evidence on the team-serving bias by analysing comments of players and coaches in newspaper articles on major sports events. In a meta-analysis of 22 questionnaire-based studies in sports settings, Mullen and Riordan (1988) found evidence for the self-serving bias, with its magnitude being larger for teams than individual athletes. Martin and Carron (2012) compared studies using questionnaires based on the attribution dimensions of Weiner's theory and those using the team-oriented attribution scale developed by Greenlees et al. (2005). They confirmed the robustness of the team-serving bias. While most of the previous evidence on the attribution effect in sports is based on surveys of athletes after competitions, we also find behavioural evidence supportive of this effect during competitions. Our results further show that the likelihood of dissents decreases with the number of prior cards the opponent team received. This finding could be explained by the fact that motives for dissents include misconducts by the opposing team that are not sanctioned by the referee. Hence, the more often the opponent is sanctioned, the lower the incentive for dissents against the referee.

The higher likelihood of dissent for away teams we observe in our data could indirectly hint to a home bias of referees, i.e. a favourable treatment of the home team by the referee, which has been found in numerous studies (Buraimo et al., 2010; Buraimo et al., 2012; Dawson and Dobson, 2010; Dawson et al., 2007; Dohmen, 2008; Garicano et al., 2005; Page and Page, 2010; Sutter and Kocher, 2004) . In experimental studies, van Prooijen et al. (2008) and Verboon and van Dijke (2011) show that the procedural fairness of an authority implementing a sanction system increases compliance with the authority. In the context of our study, this could lead to away team players perceiving the favourable treatment of the home team by the authority (the referee) as unfair, and result in their reduced compliance with the authority (more protests against the referee's decisions).

We find that all misconducts are negatively affected by the number of yellow cards the team has previously received, which could be interpreted as a deterrence effect of previous sanctions of the own team (Buraimo et al., 2010). This indicates that (severe) punishment might mitigate illegal behaviour, as predicted by theory (Gilpatrick, 2011).

We also find some noteworthy results on the behaviour of captains and regular players. Regular players are more likely to engage in sabotage when the opponent team has recently conducted a severe misconduct. Such retaliative foul plays, however, cannot be observed for captains. An explanation could be, e.g., that team leaders are more capable of controlling their emotions (Dupuis et al., 2006). The result is also in line with the finding of Price and Weiss (2011) that peer leaders are characterised by better behavioural conduct. Furthermore, captains seem to react quickly to sanctioning of their teammates by challenging the referee's decision. Although captains do not have any privileges allowing them to challenge the referee according to FIFA's Laws of the Game, they are often seen to be responsible for their team's behaviour and as a spokesman for their team before the referee. Our data indicate that captains live up to this role by challenging unfavourable referee decisions more frequently, even though it increases their own chances of being cautioned.

Furthermore, the likelihood of captains challenging referees' decisions and engaging in sabotage increases in important games. This finding could be related to the effect of prize spread on the behaviour of contestants: the wider the prize spread, the higher the incentives to engage in sabotage (Chowdhury and Gürtler, 2015). Garicano and Palacios-Huerta (2014) and del Corral et al. (2010) provide evidence for increased sabotage after the points for winning a football match were increased from two to three. The covariate competitiveness could measure a similar effect. A match against a neighbouring team in the table, particularly towards the end of the season, not only provides the chance to receive three points for the own team, but also to deny three points to a direct competitor in the table (making the game a so called 'six-pointer'), which is a widening of the prize spread compared to other matches. In this regard, increased sabotage is a rational strategy in the case of a high prize spread. In this vein, the higher experience and age of team captains as well as their higher capability to control their emotions (Dupuis et al., 2006; Fransen et al., 2014) might result in 'more rational' behaviour compared to regular players.

In line with previous evidence, our findings show that the impact of illegal behaviour on team outcome likely is negative or non-existent at best. Nonetheless, players do engage in both dissents and sabotage. Deutscher and Schneemann (2017) argue that this self-damaging behaviour could be driven by players perceiving any action as better than inaction, as the latter could be interpreted as giving-up by observers (Grund et al., 2013). Hence, particularly weaker teams could use sabotage too extensively in order to signal effort.[9]

6. Conclusion

We examined sanctioned misconducts in sports contests. The analyses presented here extend previous insights into behaviour in contests in two ways: (i) we explicitly differentiate between destructive actions directly aimed at the opposing team, i.e. fouls sanctioned with a yellow card, and (ii) protesting behaviour aimed at the authority responsible for enforcing the rules of the contest, i.e. dissents sanctioned with yellow cards. This differentiation allows for a more precise analysis of sabotage in sports contests. A main result of our analysis of misconducts against the opposing team is that contestants with lower ability engage more in sabotage than stronger teams. This confirms theories on sabotage in contests and is in line with previous empirical

[9] In addition to the direct effect on match success, severe misconducts might negatively affect success in future matches. Typically, players are suspended for at least one match if they received a certain amount of yellow cards in the previous matches of that season. Hence, misconducts can negatively affect team performance in more than just the current match.

findings. However, we do not find this effect of ability on dissent with the referee.

With respect to dissents, we find that protesting against the referee increases in the case of an unfavourable score. An explanation for this behaviour could be self-serving (or team-serving) attribution. In contrast, we find an inverted U-shaped relationship between the goal difference and the probability of sabotage. Furthermore, away teams dissent more, which could be due to home-biased referees.

We further distinguish between the behaviour of captains and other players in the team. Our results indicate that captains are more likely to dissent with the referee and engage in sabotage in particularly important matches. Also, captains do not seem to participate in escalations of foul play, which is in line with previous findings that team captains seem more capable to control their emotions. However, captains are more likely to dissent with the referee if their own team has recently been sanctioned.

Tournaments in other contexts, e.g. tournaments within firms, are often installed to provide incentives to exert effort or to select the best contestants. However, in line with previous findings, our results show that contests also incentivise undesirable sabotage. At the same time, illegal behaviour seems to be detrimental for team success. A possible measure to prevent or at least to reduce sabotage is punishment. Our results show that previous sanctions of illegal activities of a team, i.e. the number of yellow cards a team received prior to the subject minute, reduce the probability of misconduct. This indicates that punishments of team members, at least if they can be observed, also lead to a reduction of illegal activities in non-punished individuals.

In spite of its detailed controls for within-match dynamics, our study has limitations. Analyses based on misconducts actually sanctioned only contain illegal activities observed and interpreted as illegal by the referee. Hence, our data include wrong referee decisions (false positives), lack activities not sanctioned by the referee (false negatives). Thus, one interesting aim for further research is to include information on wrong referee decisions and unpunished sabotage. This information could further prove meaningful in explaining players' dissents with the referee and provide insights into how the effectiveness and fairness of punishment of sabotage affects behaviour in contests.

A. Appendix

Table 5: Allocation of all 227 matches across European leagues

Country	No. of matches in the respective league		
	first league	second league	third league
Austria	15	15	4
England	13	-	-
Germany	60	38	42
Spain	16	-	-
Switzerland	21	-	-
Turkey	3	-	-

Table 6: OLS Regressions with final score (goal difference at the end of the match) and ordered probit regressions with match result (loss, draw, win) as dependent variables

	(1) Final Score	(2) Match Result	(3) Final Score	(4) Match Result
Difference in bookmaker probability	0.9038**	0.9583**	1.0275**	1.0528***
	(2.24)	(2.38)	(2.58)	(2.66)
Attendance	-0.4211	-0.1769	-0.4959	-0.2413
	(1.40)	(0.61)	(1.65)	(0.83)
Derby	0.5124	0.4126	0.4843	0.3847
	(1.24)	(0.93)	(1.19)	(0.86)
Minutes stoppage time	0.0021	0.0898	-0.0279	0.0688
	(0.03)	(0.99)	(0.38)	(0.75)
Difference in shots on target	0.1879***	0.1226***	0.1841***	0.1244***
	(4.90)	(3.11)	(5.21)	(3.25)
Difference in all yellow cards	-0.1457**	-0.1603***		
	(2.59)	(2.64)		
Difference in dissents			-0.3040***	-0.3176***
			(2.90)	(2.84)
Difference in other misconducts			-0.0753	-0.0878
			(1.21)	(1.40)
Observations	117	117	117	117
R^2	0.516		0.535	
Pseudo R^2		0.270		0.285

Notes: Absolute t-statistics (OLS) and z-statistics (ordered probit) in parentheses. Robust standard errors. Significance: * p<0.10, ** p<0.05, *** p<0.01.

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Chapter 5

Generalists vs. Specialists: Skill Variety and Remuneration in Football

Reference for this Paper:

Kempa, Karol (2018), “Generalists vs. Specialists: Skill Variety and Remuneration in Football”, mimeo.

Conferences with Review Process:

3rd International Conference – Sport Economics & Sport Management, Vienna, 2018.

Generalists vs. Specialists: Skill Variety and Remuneration in Football*

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April 2018

Abstract

This paper extends the existing literature on the remuneration of generalists versus specialists by providing new evidence on the impact of skill variety on remuneration based on professional sports data from the German *Bundesliga*. A specific advantage of football data for the analysis is that it allows for a precise measurement of the specialisation of players in certain skills/tasks. In football, there are three main field positions – defender, midfielder, and forward – that can be further subdivided into twelve tactical (sub-)positions. These positions can be interpreted as specific tasks in team production. I construct three measures of skill variety, which reflect whether a player is rather a specialist in one task or a generalist, able to perform several tasks. I use OLS and quantile regressions to investigate how skill variety affects player salaries. Defenders and forwards receive a return on skill specialisation, while midfielders do not to profit from skill specialisation. An explanation for the findings could be that defenders and forwards have more specialised tasks in the football match compared to midfielders. While the latter are almost equally engaged in offensive and defensive plays, the former two groups mainly perform either defensive or offensive tasks. Overall, the findings indicate that employees receive returns to specialisation. These returns disappear for occupations involving a wide range of tasks, indicating a trade-off between specialising on certain tasks and skill versatility.

Keywords: Football; Generalists; Salary; Specialists; Task-Specific Human Capital.

JEL-Codes: J24, J31, Z22.

*I would like to thank Guido Bünstorf, Christian Haas, Laura Kempa, Sebastian Krügel, Johannes Lips, Jürgen Meckl, and Ulf Moslener and for very helpful comments on this paper. Dania Eugenidis, Jonas Possmann, Louisa Rabast, Stephanie Roigk, and Nils Vitu provided excellent assistance in compiling the dataset used in this study. All remaining errors are, of course, my own responsibility.

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1. Introduction

At the beginning of his study of the *Wealth of Nations*, Adam Smith (1776) discusses the causes and positive effects of the division of labour and specialisation, namely that productivity can be enhanced by concentrating on fewer tasks. Becker and Murphy (1992) argue that there are returns to specialisation, as the returns to time spent on performing certain tasks are larger for employees focussing on fewer tasks. More recently, Lazear (2004, 2005, 2012) proposed that wage employment should benefit specialised skill sets with the exception of employees in leadership roles that profit from being generalists. However, the empirical evidence on the labour market success of generalists versus specialists is rather mixed with (i) evidence for returns to specialisation (Aldén et al., 2017; Åstebro and Thompson, 2011; Simmons and Berri, 2009), (ii) returns to being a generalist (Coenen et al., 2015; Custódio et al., 2013; Datta and Iskandar-Datta, 2014; Leighton and Speer, 2017) and (iii) studies without clear results for either (Artz et al., 2014; Åstebro et al., 2011; Hartog et al., 2010; Parey, 2016). This paper provides new evidence on the impact of skill variety on remuneration based on the concept of task-specific human capital.

In his seminal work on human capital theory, Becker (1964) proposed a distinction between general and firm-specific human capital. The former comprises general skills, such as education or work experience. The latter is human capital that is specific to a certain firm and cannot be transferred between firms. Other concepts of human capital are occupation- and industry-specific human capital. Similar to firm-specific human capital, these types of human capital cannot be transferred across occupations and industries. Gibbons and Waldman (2004, 2006) suggest another concept of human capital: task-specific human capital, which they define as a worker's ability to perform a certain task. This type of human capital can be transferred between occupations, firms, and industries. The main idea is that task-specific human capital is accumulated on the job by performing certain tasks through learning-by-doing. Clement et al. (2007) show that past experience in performing a certain task increases human capital specific to this task. Furthermore, task-specific human capital is an important driver of overall worker productivity (Cook and Mansfield, 2016). Previous evidence indicates that, next to occupation-specific human capital and work experience, task-specific human capital is an important driver of individual salaries (Gathmann and Schönberg, 2010; Schulz et al., 2013).

This paper investigates whether the dispersion of task-specific human capital or skills affects an employee's remuneration. The basic idea is as follows. The more an employee focuses on one of very few tasks, the higher is their productivity in that task(s) due to learning-by-doing. Such an employee could be referred to as a specialist. In contrast, consider an employee, who has performed a larger variety of different tasks, but each of them less often than the aforementioned specialists (given the same level of work experience). Such an individual would have less specific human capital in each task, but is able to perform a larger variety of tasks and hence would rather be more versatile, i.e. a generalist. The questions this paper tries to answer are: Are specialists or generalists more valuable for the employer and thus receive higher salaries?

Does the effect of the variety of task-specific skills on salary differ across occupations with heterogeneous skill requirements?

This paper analyses the effect of the dispersion of task-specific human capital on remuneration of employees based on data from the German *Bundesliga* and adds to the previous literature in the following ways. I use a measure of skill variety that is based on task-specific human capital. So far, studies on the remuneration of generalists versus specialists have focussed on other concepts of human capital, i.e. occupation- or industry-specific human capital, or other measures as cognitive abilities or college degrees. Second, it is among the first contributions using professional sports data.[1] A specific advantage of football data for this analysis is that it allows for a very precise measurement of task-specific human capital, which is rather difficult in a general labour market context. Due to the observability of employees' (athletes') attributes in sports data (Kahn, 2000), it is further possible to control for factors, such as actual performance or specific talents of individuals.

Task-specific skill specialisation is measured as follows. In association football, there are three main field positions – defender, midfielder, and forward – that can be interpreted as different occupations in a football team.[2] These can be further subdivided into twelve tactical (sub-)positions.[3] These positions can be interpreted as specific tasks in team production. Based on the idea that task-specific human capital is accumulated through learning-by-doing, the number of matches a player has played on each of these positions can be interpreted as their specific skill in performing the respective task. I construct measures of task-specific skill variety for each player, which reflects whether a player is rather a specialist in one task or a generalist that is able to perform several tasks. I then investigate whether the dispersion in task-specific human capital affects salaries.

For all measures of skill variety, the base results indicate that the degree of skill specialisation has a positive effect on earnings, i.e. more specialised players receive higher salaries. When differentiating between occupations, I find that defenders and forwards receive a salary premium if they are more specialised than the average player on the respective main position, while the result are substantially different for midfielders. Midfielders receive neither a return on task-specific skill versatility, i.e. for being generalists, nor a return for skill specialisation, i.e. for being a specialist. An explanation for this result could be that defenders and forwards require more specialised skill sets in the football match compared to midfielders. While the latter are almost equally engaged in offensive and defensive plays, the former two groups mainly perform

[1] An exception are Simmons and Berri (2009), who study skill specialisation of running backs in the National Football League (NFL). Furthermore, Franck et al. (2011) focus their empirical analysis based on data from the German *Bundesliga* on general and team-specific human capital and thus have a complementary focus to this study.

[2] Alternatively, one could argue that being a football player is an occupation. But as defenders, midfielders, and forwards have different and distinct roles in a football team, these main positions can be referred to as different occupations within a football club (firm). This definition of main positions as occupations is, however, not critical for this analysis.

[3] The positions are left-, right-, and centre-back; left-, right-, defensive-, central-, and attacking midfield; left-, right wing, secondary striker, and central forward.

defensive or offensive tasks. Hence, it is not surprising that forwards and defenders profit from a higher degree of specialisation. When transferred to the general labour market context, these findings indicate that specialisation is more beneficial for employees, as there are no returns from skill versatility even in occupations with a wide range of tasks. For occupations involving a wider range of tasks, there seems to be a trade-off between skill specialisation and versatility.

The paper is structured as follows. Section 2 provides a literature review on skill dispersion and employee remuneration. Section 3 presents the institutional setting for the empirical analysis and provides an overview of the data and the estimation approach. Section 4 presents the empirical results. Section 5 discusses the findings and concludes.

2. Previous Literature on Specialists, Generalists, and Remuneration

Various strands of literature have analysed the compensation of generalists versus specialists. One strand of literature is based on a theory by Lazear (2004, 2005). He proposed that generalists are more likely to become entrepreneurs, while individuals specialised in certain tasks are more likely to become employees. He argues that entrepreneurs should have some ability or human capital in a variety of tasks. Entrants into self-employment typically have to perform various tasks themselves and even when hiring specialists for certain tasks, entrepreneurs need some basic knowledge in the respective task to be able to assess the applicants. In contrast, employees typically perform one (or few) task(s). As they are paid based on their productivity in performing the task, it is beneficial for workers if they are specialists.[4]

Based on Lazear's *Jack of all trades* theory, several studies analysed individuals' choices between entrepreneurship and employment and their resulting earnings based on their skill variety. As this paper focuses on employees, empirical results on entrepreneurs are not discussed. Using the responses of 830 independent inventors to a survey conducted in 2004, Åstebro and Thompson (2011) investigate how the number of industries and occupational fields the respondents have previously worked in affect income. For employees they find that the number of previous occupational fields negatively affects income, which indicates that employees benefit from higher specialisation. Åstebro et al. (2011) conduct a similar analysis on employees using data from the Korean Labor and Income Panel Study (KLIPS) and find the overall number of prior job changes negatively affects earnings of employees. The authors decompose job changes into within-employer changes in occupation, within-occupation changes of the employer, and simultaneous changes in employer and occupation. The latter two components negatively impact remuneration and thus indicate that skill specialisation leads to higher earnings. For within-employer changes in occupation, Åstebro et al. (2011) find a positive effect on salaries and argue that this finding is probably driven by promotions within the firm that often lead to occupational

[4]Lazear (2005) provides evidence for this theory based on transcripts of Stanford MBA alumni and employment experiences of individuals. He finds that individuals with higher variety in their curriculum in the MBA studies and those who had more roles in their employment history are more likely to become entrepreneurs. Hence, more specialised individuals do rather choose to become / remain in employment. Wagner (2006) finds similar results based on a survey of 12,000 individuals in Germany.

changes. Bublitz and Noseleit (2014) expand the aforementioned approaches by distinguishing between different firm sizes. The main idea is that skill sets should be more balanced in smaller firms, as employees typically take over more tasks. In contrast, task complexity increases with firm size, which should induce a specialisation in fewer tasks. Using data from a 2006 Employment Survey, conducted by the Federal Institute for Vocational Education and Training (BIBB) and the Federal Institute for Occupational Safety and Health (BAuA) in Germany, the authors confirm this hypothesis. With respect to compensation, Bublitz and Noseleit (2014) find that employed generalists overall receive a premium, while the magnitude of the skill balance's impact on earnings decreases when business size increases.

In contrast to Åstebro and Thompson (2011) and Åstebro et al. (2011), who use employment histories that could be interpreted as firm-, occupation-, or industry-specific human capital, other studies base their analyses on cognitive abilities. Hartog et al. (2010) use cognitive test scores from the Armed Services Vocational Aptitude Battery (ASVAB) and data from the National Longitudinal Survey of Youth (NLSY) to derive five measures of specific abilities.[5] In order to measure the balance of skills, the authors calculate a coefficient of variation across the specific abilities to measure dispersion of skills. Their findings indicate that a balanced set of skills increases earnings of entrepreneurs, as predicted by Lazear's theory. For employees, however, the authors do not find any effect of skill dispersion on income, i.e. no evidence for the hypothesis that employees profit from being specialists. Aldén et al. (2017) conduct a similar analysis. Their measure of balance in abilities is calculated as the standard deviation in individual scores on five tests conducted during Swedish military enlistment. In contrast to Hartog et al. (2010), the authors find a negative effect of balanced skills on earnings if employees, i.e. employees profit from specialisation.

Another strand of literature originates from the analysis of the labour market returns to university degrees. One potential core driver of differences in the returns across university degrees, which is investigated in this literature, is the degree of specialisation. Artz et al. (2014) analyse this issue based on a sample of alumni with various agricultural degrees. The authors find that graduates from more specialised degree programmes earn more within the agricultural sector, while those having more generalised degrees, i.e. degrees from programmes with broader curricula, earn a salary premium in other non-agricultural sectors. Kinsler and Pavan (2015) also find salary premiums for being employed in jobs related to studies, in particular for science-related majors. Coenen et al. (2015) compare several narrow (more specialised) and broad (more generalised) vocational education programmes in the Netherlands with respect to their effect on the respective graduates' labour market returns. Overall, the authors find that specialists earn less compared to generalists. This result even holds when specialised graduates have a job within their occupational domain, but is particularly strong when specialists are employed outside that domain. Leighton and Speer (2017) use four different measures of specialisation and find that generalists receive the highest salary premiums throughout their careers.[6] Particularly majors

[5]These are language or verbal ability, mathematical ability, technical ability, clerical ability, and social ability.

[6]The measures are an occupational Herfindahl-Hirschman Index (HHI), a curriculum HHI, a vocational indicator,

that teach skills that are highly transferable across occupations lead to premiums. Specialisation, however, only pays off in the short run. Rather than comparing different college majors, Parey (2016) compares the labour market success of graduates from vocational education with those doing a firm-based apprenticeship. The latter can be considered more specialised as they are provided by firm that has an incentive to invest in human capital that is specific to the apprentices' tasks in the firm. There are, however, no differences with respect to their returns on the labour market.

A third strand of literature focuses on top management. Lazear (2012) proposes a human capital theory of corporate leadership, which is related to the theory of entrepreneurship versus employment discussed above (Lazear, 2004, 2005). The core idea is that leaders within a firm, i.e. (top) management, are confronted with a high variety of different problems and choices and hence profit from a broader skill set.[7] Frederiksen and Kato (2017) and Lazear (2012) provide empirical support for this theory of corporate leadership, i.e. a higher variety of skills, mainly through broadening human capital, increases the likelihood to be appointed in top management. Lazear (2012) further shows that the quantity of previously experienced roles positively affects the compensation of top management. Custódio et al. (2013) and Datta and Iskandar-Datta (2014) provide further support. Custódio et al. (2013) construct a general ability index for CEO's, which includes, e.g., the number of firms and industries where the CEO worked as well as the number of positions the CEO previously held. The authors find the generalist CEOs earn a compensation premium. Datta and Iskandar-Datta (2014) focus on CFO compensation and find that CFOs with elite MBA degrees (generalists) earn a premium compared to CFOs with other non-MBA degrees or professional accounting certification (specialists).

3. Empirical Framework

Overall, previous findings on the remuneration of generalists and specialists are very mixed indicating that this issue is still not fully understood. Furthermore, none of the previous studies base their measurement of skill specialisation on task-specific human capital. This paper aims to fill this gap in the literature by constructing a measure of skill specialisation based on the

and a Theil measure. The occupational HHI is based on the distribution of graduates in a major across different occupational fields. The higher the value of this measure, the higher is the concentration of graduates in one / few occupations and hence the more specialised is this major. The intuition behind the curriculum HHI is similar: the fewer courses from other fields than the major, the more general is the major. The vocational measure is based on the National Center for Education Statistics. The authors interpret majors classified as academic as general, while career or career technical majors are interpreted as vocational (specialised). The Theil measure captures the transferability of graduates' skills across occupations, by measuring the differences in returns to a major in different occupations.

[7] Gibbons and Waldman (2004) use a similar argument in their theory on task-specific human capital. Assuming that employees accumulated task-specific human capital, when performing certain tasks, job rotation may be useful tool for future managers. By moving from job to job, management candidates gain knowledge on a variety of different tasks, which is useful for supervising employees on lower levels that actually perform those tasks. Murphy and Zábojník (2004) propose a theory predicting that CEOs should receive a compensation premium for general skills that are not firm-specific.

concept of task-specific human capital. I first introduce the institutional setting of this study and discuss the advantages of using a professional sports setting for this analysis. I then present the data used in the empirical analysis and describe the estimation approach.

3.1. Institutional Setting

The institutional setting is the top level of professional association football in Germany, namely the *Bundesliga*.[8] There are 18 teams in the Bundesliga, each of them playing 34 matches in one season, i.e. twice against each team in the league. The team ranked first in the table at the end of the season wins the championship, while up to three teams (ranked last in the table) get relegated to the second division. In a football match, there are eleven players on the pitch, while the total team rosters are larger (unlimited) and typically range between 25 and 35 players. Clubs hire players, who typically get offered contracts with a specific duration and negotiate their salaries with the respective club. If the player wants to transfer to another club before the contract expires, the current club (employer) has the right to veto the transfer and require a transfer fee from the potential new club (Feess et al., 2015). Since the so-called *Bosman Judgement* in 1995, players are free to move to other teams after their contract has expired.[9] Overall, the *Bundesliga* resembles other European football leagues, while there are key aspects that differ compared to US professional sports leagues. The latter are structured to promote a competitive balance among competing teams through, e.g., salary caps and a draft system for rookie players (Torgler and Schmidt, 2007). In contrast, there is more active transfer markets and less regulated salaries in European top football leagues, as the *Bundesliga*.

Advantages of studying labour markets based on sports data are the observability of attributes, performance, and earnings of workers (athletes) and the quality of statistics that are often more accurate and detailed than typical microdata (Kahn, 2000). Thus, a professional sports setting provides a unique laboratory for labour market research as many factors that cannot be observed in other labour markets, such as the abilities of employees or their actual performance in team production, can be controlled for in this field environment. This allows a clearer isolation of specific effects. However, a professional sports context also has unique attributes compared to other labour markets, such as, on average, very high salaries, and the fact that individual performance in team production is observed by thousands of spectators in stadiums (Franck and Nüesch, 2011). These specific attributes of labour markets in professional sports limits the generalisably of findings (Harder, 1992). The applicability of my findings based on the professional football setting to a general labour market context are discussed in Section 5.

Thus, numerous studies have investigated various determinants of remuneration based on professional football data (See Frick (2007) for a review). These include the role of scarce talent (Bryson et al., 2013), migration (Bryson et al., 2014), player popularity (Franck and Nüesch,

[8] There are two further national leagues in German club football, i.e. the second division, *2. Bundesliga*, and the third division, *3. Liga*.

[9] See Court of Justice of the European Communities, Case C-415/93. Prior to this judgement, a club could demand a transfer fee even when the contract has expired.

Table 1: Main field positions and their (sub-) positions

Defender	Midfielder	Forward
Centre-Back (CB)	Defensive MF (DM)	Secondary Striker (SS)
Left- / Right-Back (LB / RB)	Central MF (CM)	Centre Forward (CF)
	Attacking MF (AM)	Left / Right Wing (LW/ RW)
	Left / Right MF (LM / RM)	

2012; Garcia-del-Barrio and Pujol, 2007; Lehmann and Schulze, 2008; Lucifora and Simmons, 2003), the consistency of performance (Deutscher and Büschemann, 2015), or firm-specific and general human capital (Franck et al., 2011). To the best of my knowledge, the only empirical study that investigates the returns to specialisation compared to versatility in a professional sports setting was conducted by Simmons and Berri (2009) using data on running backs in the NFL. The authors consider skills to perform two main skills of running backs, namely rushing and pass reception, and find that running backs specialised in one of two skills have higher returns than more versatile players. This paper adds to previous findings by simultaneously analysing different main positions (occupations) with potentially different skill sets required, while Simmons and Berri (2009) focussed on one position. Furthermore, players in the NFL typically only play on one position that requires very specialised skills. In association football, however, the level of specialisation varies across players and thus seems a more suitable setting to draw conclusions for other labour markets.

A specific advantage of football data for this analysis is that it allows for a very precise measurement of task-specific specialisation of players. In football, there are three main field positions: defender (DE), midfielder (MF), and forward (FW). These positions can be further subdivided into twelve tactical (sub-)positions, as depicted in Table 1. Goalkeepers are not included in this analysis, as they only perform one task and mature professional goalkeepers do not switch to any other positions.

These positions can be interpreted as specific tasks in team production. The skill to perform each task, i.e. task-specific human capital, is accumulated by performing the respective task (Gibbons and Waldman, 2004). Thus, in the professional football setting of this study, the number of matches a player has played on a certain position in his career prior to the respective season can be interpreted as the player's human capital to perform this specific task that he has accumulated through learning-by-doing. In addition to on-field learning, the number of matches played on a position also reflects the player's ability to perform this specific task, as coaches select the, in their opinion, best player to appear in matches on certain positions (Simmons and Berri, 2009). The number of career matches played on all possible positions reveals whether the player is specialised on one or few positions or whether a player has a more versatile skill set, but a lower skill-intensity per position.[10] I construct different measures of skill variety for each

[10]Two examples help to illustrate the information used. Prior to the 2015/16 season, Robert Lewandowski (forward, Bayern Munich) played 92% of all his career matches as central forward, 7% as secondary forward, and 1% as attacking midfielder and hence is rather specialised. In contrast, Zlatko Junuzovic's (midfielder, Werder Bremen) career match distribution is as follows: 37% attacking midfield, 18% left midfield, 13% left wing,

player, which reflect whether a player is rather a specialist in one task or a generalist, able to perform several tasks. I then investigate how the skill variety, controlling for individual player characteristics as well as club- and season fixed effects, affects player wages.

3.2. Data

The database of this study covers the seasons 2010/11 - 2016/17 of the German *Bundesliga*. Most of the information on salaries and player characteristics was gathered from *Kicker*, a highly respected German football magazine. From this source, I collected information on player performance (based on expert evaluations), experience (age, career matches in the national team, season matches as starter/substitute in the *Bundesliga*, and main position). I use data from the website *www.transfermarkt.de* on the number of career matches the athletes have played on a certain position and the footedness of players.[11] Both data sources have frequently been used in previous empirical studies (Battré and Höhmann, 2011; Bryson et al., 2013; Deutscher and Büschemann, 2015; Franck and Nüesch, 2011; Frick, 2011; Lehmann and Schulze, 2008; Torgler and Schmidt, 2007). Combing the data from these sources yields an unbalanced panel dataset with 2002 player-year observations. A more detailed description of all dependent and explanatory variables is presented below.

3.2.1. Salary

Following the literature, I use market valuations of *Kicker* as a proxy for player salaries that are largely undisclosed (Bryson et al., 2013; Deutscher and Büschemann, 2015; Franck and Nüesch, 2011; Frick, 2011; Lehmann and Schulze, 2008). As previous studies, annual salary in season t is approximated as the *Kicker* valuation in season t divided by a factor of 1.5. These market valuations are likely to be consistent, as it has been systematically estimated over several years (Torgler and Schmidt, 2007). First proxies of market values were published by the magazine in the mid-1990s (Franck et al., 2011). Franck and Nüesch (2011) have investigated the reliability of the *Kicker* data by comparing it to estimates from *www.transfermarkt.de*.[12] They find a correlation between the market value estimates of *Kicker* and market value estimates from *www.transfermarkt.de* of 0.89. Torgler and Schmidt (2007) find a correlation coefficient of 0.83. Frick (2006) compares the salary estimates from *Kicker* to a sample of actually observed salary data for two seasons of the *Bundesliga* and finds a correlation of 0.8. Thus, the market valuations by *Kicker* can be deemed a reliable proxy for player salaries.

11% left midfield, 10% defensive midfield, 5% central midfield, 5% right wing, and 1% secondary striker. Thus, he is rather a generalist.

[11] For the footedness of players, I also use hard copies of the German sport magazine *Sportbild* to cross-check and supplement the data.

[12] On this website, market values are updated based on actual past transfer values, the players' performance, age, injuries, etc. The estimates of the market values are determined by registered users together with moderators of the respective forums and thus are based on a "wisdom of the crowds" principle (Gerhards et al., 2014). Gerhards et al. (2014) compared market value estimates from *www.transfermarkt.de* with transfer fees of actually performed transfers and found a correlation of 0.93 indicating a high reliability of the estimates.

Figure 1: Density estimates of annual player salaries

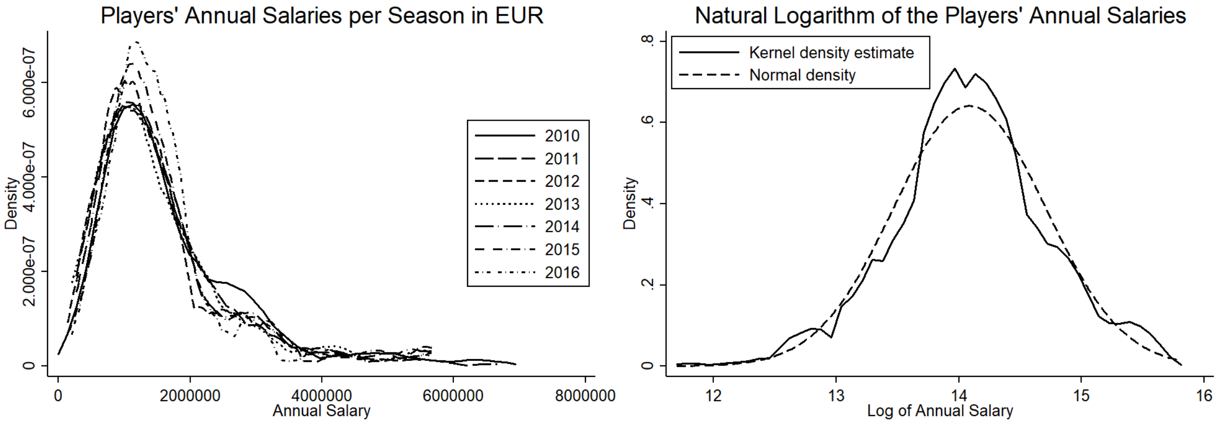


Figure 1 (left panel) shows density estimates of players' annual salaries by season. The distribution has the typical attribute of many income distributions, i.e. a long high-income tail. Thus, I use the natural logarithm of annual salaries as the dependent variable in the analysis (*Log of Annual Salary*). The distribution of *Log of Annual Salary* better resembles a normal distribution, as can be seen in the right panel of Figure 1.

3.2.2. Measuring Skill Specialisation

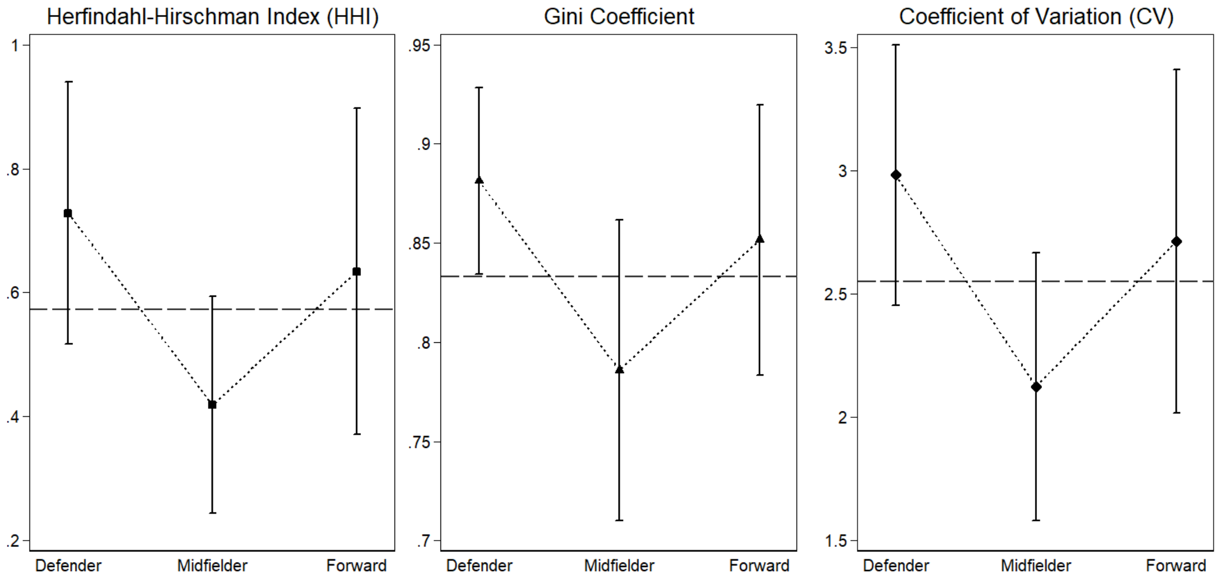
The measure on skill variety is based on information on the number of matches a player has played on each of the twelve positions prior to the respective season. As outlined in Subsection 3.1, the number of career matches on a certain position are proxies for the players' accumulated task-specific human capital to perform the respective tasks. For robustness, three alternative measures of skill variety for each player are calculated based on the data. All three metrics have in common that the metric for a specific season is based on the players' career matches prior to the season.

As a first measure, I calculate the Herfindahl-Hirschman Index (HHI) to measure the concentration of task-specific skills, which has been used as a measure of the specificity of college majors in previous related studies (Blom et al., 2015; Leighton and Speer, 2017). The HHI of player i in season t is calculated as follows:

$$HHI_{it} = \sum_{p=1}^{12} s_{ipt-1}^2,$$

where p denotes each of the twelve available positions and s_{ipt-1} is the share of career matches played on position p relative to total career matches at the end of season $t-1$. This measure varies between 0 and 1 and the higher the skill concentration, i.e. the more specialised the player is, the higher is the HHI. A value of 1 would mean that the player has only played on one position in his career prior to season t.

Figure 2: Means of skill specialisation by main position measured by HHI, Gini, and CV. The horizontal dashed line is the overall mean.



As a second measure, I use the Gini coefficient, which is a common metric to measure inequality, typically in income distributions.[13] Similar to the HHI, the Gini coefficient also varies between 0 and 1. A value of 0 would indicate complete equality, i.e. a player has played the same number of matches on all possible positions in his career. The higher the Gini coefficient, the higher the inequality in the skill distribution, i.e. the more specialised is the player. Finally, I also compute the coefficient of variation (CV), which has been previously used as a measure of ability balance in the literature (Hartog et al., 2010). The CV is defined as the ratio of standard deviation to the mean. In this case, it is the standard deviation of the skill distribution, i.e. the distribution of career matches over all possible positions, divided by the mean of career matches per position. Higher values of the CV indicate a more pronounced task specialisation.

Figure 2 shows the means of all three metrics for defenders, midfielders, and forwards. The horizontal dashed line is the respective mean for the whole sample irrespective of main position. As can be seen for all three metrics, midfielders are on average more versatile players compared to defenders and forwards, which is, among other things, due to the fact that there are more (sub-) positions that midfielders can play compared to defenders and forwards. This means that the variety of relevant tasks to be performed is larger for the former players. To account for this, I adjust the metric for skill specialisation by dividing them for each individual player by the respective seasonal position mean. Thus, the variables that are used in the empirical analysis – *HHI*, *Gini*, and *CV* – measure the degree of specialisation or versatility relative to the mean of the respective main position in the respective season. In robustness checks, however, I use the absolute values of those metrics – *HHI (Absolute)*, *Gini (Absolute)*, and *CV (Absolute)*.

[13] I use the Stata Module *lorenz* to estimate Lorenz curves and compute the Gini coefficients (Jann, 2016).

3.2.3. Other Explanatory Variables

In addition the measures of specialisation in task-specific human capital, I include several control variables to account for players' experience and physical condition, namely the age (*Age*), the number of matches played for a professional club (*Total Club Matches*)[14], and the number of appearances in the national team (*Total National Matches*). Furthermore, *Age Squared* is included as the relationship between age and remuneration is likely to be non-linear. While experience increases with age and thus is expected to positively affect remunerations, player's physical abilities decrease with age, which has the opposite effect.

I further include the number of matches a player has actually played in the season. Typically the teams head coach decides, which athletes are playing in a season match. A high number of appearances indicates that the player is important from the coach's perspective. Furthermore, only players actually appearing in matches actively affect the team's success. Thus, I expect that the number of appearances in a season positively affect remuneration. For the analyses, I split up all appearances in a season into matches, where the player was in the starting line-up (*Season Matches Starter*), and the number of matches, where he was substituted in (*Season Matches Substitute*).[15] While the expected positive effect holds for the former, it is less clear for the latter. A higher number of (*Season Matches Substitute*) might also imply that the player is rather a backup and not first choice. This disaggregation allows to control for this possibility.

As a measure of actual on-field performance, I use expert evaluations from the football magazine *Kicker*. Experts of *Kicker* evaluate individual match performances for every player that has been on the pitch for at least 30 minutes (Franck and Nüesch, 2010). The performance rating is based on the German school grading system from 1.0 (very good) to 6.0 (insufficient). Expert evaluations, in particular of Kicker, have been widely used in previous studies (Bryson et al., 2013; Carrieri et al., 2017; Deutscher and Büschemann, 2015; Franck and Nüesch, 2010, 2011; Frick, 2011). For the empirical analysis, I use the average Kicker grade a player received in a season and, for ease of interpretation, subtract this average grade from 7, such that a higher value means better performance. Previous studies using these evaluations have shown that expert ratings notably differ between positions, e.g. goalkeepers tend to be rated substantially better than midfielders and defenders, while forwards receive, on average, the lowest grades (Battré and Höhmann, 2011; Deutscher and Büschemann, 2015; Franck and Nüesch, 2010). Thus, following Battré and Höhmann (2011), Bryson et al. (2013), and Franck and Nüesch (2010, 2011), I adjust the *Kicker* evaluations by dividing it by the mean of the player's respective main position average in the respective season in order to eliminate any potential positional biases in the rating. Thus, the variable (*Performance*) measures the average position adjusted performance in a specific season.

[14] An alternative measure would all matches played in the *Bundesliga*, but this measure does not appropriately capture experience of players that previously played professional leagues outside of Germany. However, choosing this alternative measure does not affect the models main results and yields quantitatively very similar effects to *Total Club Matches*

[15] The coach is allowed to perform three player substitutions in a *Bundesliga* match.

Table 2: Descriptive statistics

	Observations	Mean	Standard Deviation	Minimum	Maximum
Log of Annual Salary	2002	14.1	0.62	11.8	15.7
Age	2002	25.8	3.65	18	38
Age Squared	2002	677.6	192.5	324	1444
Total National Matches	2002	14.1	22.0	0	119
Total Club Matches	2002	113.9	71.8	0	491
Performance	2002	1.00	0.13	0.43	1.52
Season Matches Starter	2002	18.2	9.80	0	34
Season Matches Substitute	2002	4.18	4.26	0	27
Right Footed	2002	0.58	0.49	0	1
Left Footed	2002	0.22	0.41	0	1
Two Footed	2002	0.20	0.40	0	1
Last Season 2. Bundesliga	2002	0.093	0.29	0	1
Defender	2002	0.36	0.48	0	1
Midfielder	2002	0.45	0.50	0	1
Forward	2002	0.19	0.39	0	1
Gini	2002	1.00	0.080	0.69	1.18
HHI	2002	1.00	0.37	0.26	2.38
CV	2002	1.00	0.23	0.42	1.70
Gini (Absolute)	2002	0.83	0.078	0.54	0.92
HHI (Absolute)	2002	0.57	0.25	0.15	1
CV (Absolute)	2002	2.55	0.69	1.03	3.61

Following Bryson et al. (2013), I also introduce footedness as a measure of (scarce) ability into the model. The authors argue that footedness is to a large extent an innate ability. Most professional football players are right footed, while left- and two-footed players are rather scarce. Thus, it is possible that left-footed players receive a salary premium due to their scarce ability that makes them particularly well suited to certain positions (e.g. left back, - midfielder, or - wing). In particular two-footed players are likely to receive returns on this ability, as it gives them more opportunities on the pitch. For example, they pass and shoot with both feet and hence their actions during a football are less predictable for opponent players. Thus, I include three dummy variables – *Right Footed*, *Left Footed*, and *Two Footed* – to control for the effect of footedness on remuneration.

Like Battré and Höhmann (2011), I introduce the dummy variable *Last Season 2. Bundesliga* to control for those players who played in the second division in the previous season. Previous evidence indicates that, even when controlling for performance, talent, experience, and other player characteristics, there remain significant influences of players' main positions and club-specific effects on remuneration (Deutscher and Büschemann, 2015; Frick, 2011, 2012; Idson and Kahane, 2000; Kahane, 2012; Lehmann and Schulze, 2008). Thus, I include a set of dummies for the player's main field position – *Defender*, *Midfielder*, and *Forward* – as well as club dummies. Finally, I also include season dummies to control for time effects. Table 2 provides an overview of the descriptive statistics of all variables.

3.3. Estimation Approach

The general model used in the empirical analysis is:

$$\begin{aligned} Ln(Salary) = f(&Age,\ Age\ Squared,\ Total\ National\ Matches,\ Total\ Club\ Matches,\\ &Performance,\ Season\ Matches\ Starter,\ Season\ Matches\ Substitute,\\ &Footedness,\ Main\ Position,\ Skill\ Specialisation,\ League\ Last\ Season,\\ &Club\ and\ Season\ Effects). \end{aligned}$$

In order to avoid a possible endogeneity problem, I use the lagged values of the player's performance as well as the number of appearances (as started and substitute), i.e. the values from the respective previous season. All experience measures (age, total career matches played for a club and the national team) as well as the measure of skill specialisation are determined at the beginning of the season. In a first step, I estimate the model as described above to analyse the effect of skill specialisation for all players. In addition to this base model, I also analyse an alternative specification with interactions between the main position dummies and skill specialisation. This specification allows an investigation of the potential differences in the effect of skill specialisation on remuneration between defenders, midfielders, and forwards.

In a first step, I use ordinary least squares (OLS) regressions with robust standard errors.[16] In addition, I also use quantile regression (QR) estimations, which are based on the work of Koenker and Bassett (1978) and have been increasingly used in recent empirical analysis of remuneration based on professional sports data (Battré and Höhmann, 2011; Bryson et al., 2013, 2014; Deutscher and Büschemann, 2015; Deutscher et al., 2017; Lehmann and Schulze, 2008; Simmons and Berri, 2009).

QR estimation is a very useful tool in the context of this study due to the following reasons. As displayed in Figure 1, the salary distribution is right-skewed, i.e. there is a small number of top players that earn substantially more than their colleagues. This skewness is particularly strong in professional team sports (Deutscher et al., 2017; Lucifora and Simmons, 2003). Log salaries are typically characterised by an excess kurtosis. This can also be seen in my sample, where the log salary's kurtosis value of 3.37 exceeds 3 and thus indicates that the salary distribution is not log-normal. This non-normality of the dependent variable might violate the normality assumption for the error terms. When performing OLS regressions, standard errors and confidence intervals and thus the significance levels of the estimates might be affected. In contrast, QR estimation does not rely on the normality assumption and is thus applicable in this case (Leeds, 2014).

Another advantage of QR estimation is that it allows for valuable additional insights. QR allows an estimation of the marginal effects of the explanatory variables at different points of the dependent variable's distribution (Koenker, 2009). Within this study, I can investigate the effect of skill specialisation and other explanatory variables on remuneration at different salary

[16] White- and Breuch-Pagan tests after running OLS regressions reject the null hypothesis that the variance of the residuals is homogenous.

quantiles. While OLS coefficients are the impact of a covariate on the conditional mean of remuneration, QR estimates refer to the impact of an independent variable on salary for a specific quantile of the conditional salary distribution (Leeds, 2014).[17] QR allows for an investigation whether skill specialisation and skill versatility have different impacts on players at the lower end of the conditional salary distribution compared to the high paid top players. I estimate the 0.1, 0.25, 0.5 (median), 0.75, and 0.9 quantiles with bootstrapped standard errors.[18] For both model specifications (without and with main position interactions), I perform both OLS regressions and QRs.

4. Empirical Results

4.1. OLS Estimates

The OLS estimation results for the base model and the specification with skill specialisation by position are reported in Tables 3 and 4, respectively. Before discussing the main results, I turn to the impacts of the control variables. Overall, the effects of the control variables have the expected signs, are mostly statistically significant, and are almost identical across the measures of skill specialisation (*Gini*, *HHI*, and *CV*) and model specifications.

As predicted, the coefficient of *Age* has a positive sign, while its squared term's coefficient has a negative sign, indicating a reversed U-shaped relationship between a player's age and remuneration. The turning point of *Age* is around 25 years, i.e. the age level that maximises salary. Furthermore, all previous career appearances for clubs (*Total Club Matches*) and for the national team (*Total National Matches*) positively affect remuneration, while the effect of the latter is notably larger than the former. An explanation could be that matches for the national team could, in addition to experience, measure an additional notion of player talent, as typically the best players are nominated to play for the national team.

The number of matches played in the starting line-up in the previous season has a positive and significant effect on remunerations. The larger *Season Matches Starter*, the higher is the player's active contribution to team production resulting in a higher salary. Furthermore, the coefficient of *Season Matches Starter* is notably larger than the coefficient of *Total Club Matches* indicating that recent appearances have a stronger effect than previous career appearances. The number of matches, where the player was a backup and substituted in during the match (*Season Matches Substitute*), also has a positive effect on remuneration, which is, however, notably

[17]This is important, when interpreting coefficients of a QR. It is the impact of a certain covariate, say player's age, on the salary of a player in specific quantile of the conditional salary distribution, e.g. the 0.9 quantile. This coefficient, however, does not say anything about the effect of age on salaries for the top 10% earning players in the sample. Instead, the coefficient of the 90*th* percentile shows how an additional year of age affects the salary of a player, who earns relatively much relative to other players given their age. Leeds (2014) provides a more detailed discussion on the interpretation of QR estimates and typical misinterpretations, in particular in sports economics.

[18]I bootstrapped with 250 repetitions. Most of the recent studies on remuneration in a profession sports context bootstrap with 200 repetitions (Bryson et al., 2013, 2014; Frick, 2011; Simmons and Berri, 2009).

Table 3: The impact of task-specific skill specialisation on salary: OLS regression results

	(1)		(2)		(3)	
Age	0.2363***	(8.23)	0.2358***	(8.22)	0.2362***	(8.24)
Age Squared	-0.0047***	(-8.78)	-0.0047***	(-8.76)	-0.0047***	(-8.77)
Total National Matches	0.0029***	(6.55)	0.0028***	(6.54)	0.0028***	(6.47)
Total Club Matches	0.0014***	(8.87)	0.0014***	(8.88)	0.0014***	(8.83)
Performance	1.3731***	(13.66)	1.3723***	(13.66)	1.3739***	(13.67)
Season Matches Starter	0.0236***	(19.29)	0.0236***	(19.30)	0.0236***	(19.32)
Season Matches Substitute	0.0062**	(2.37)	0.0062**	(2.37)	0.0062**	(2.37)
Left Footed	0.0296	(1.57)	0.0291	(1.54)	0.0275	(1.46)
Two Footed	0.0435**	(2.07)	0.0434**	(2.07)	0.0413**	(1.96)
Last Season 2. Bundesliga	-0.4876***	(-13.43)	-0.4874***	(-13.41)	-0.4867***	(-13.34)
Midfielder	0.1275***	(6.96)	0.1275***	(6.97)	0.1278***	(6.98)
Forward	0.3319***	(13.38)	0.3319***	(13.38)	0.3320***	(13.37)
HHI	0.0663***	(3.25)				
CV			0.1099***	(3.28)		
Gini					0.2688***	(2.68)
Constant	9.1000***	(23.07)	9.0620***	(22.95)	8.8925***	(21.90)
Observations	2002		2002		2002	
R^2	0.698		0.698		0.697	

Notes: Club- and season fixed effects estimation with robust standard errors. The dependent variable is log of annual salary. *t*-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

smaller than the effect of matches in the starting line-up. This finding could indicate the potential opposing effects of being substituted as mentioned above: a positive effect on remuneration due to increased participation in team production and a negative effect as a higher number of matches as a substitute indicates that the player's status is rather that of a back-up player. In fact, the QR results, which will be discussed below, shed some light on this relationship as they show differences in the effect across the conditional salary distribution.

As expected, the actual performance in the previous season has a positive and highly significant effect on remuneration. There is, however, no statistically significant return on left-footedness. In contrast, players that are two-footed, i.e. can play (almost) equally well with both feet, receive a salary premium (positive and significant effect of *Two Footed*). An interpretation of these results could be that the scarcity of a talent alone, as in the case of left-footed players that make up 22% in the sample, does not entail a salary premium. Two-footedness, however, is not only a scarce talent (20% of the players in the sample), but also gives the player advantages over one footed players, whether left or right footed, on the pitch, as they can intercept, play, and shoot the ball with both feet equally well, which makes them less predictable for their opponents. Finally, midfielders and forwards receive salary premiums compared to defenders (reference category), as can be seen from the results in Table 3.

I now turn to the discussion of the main results of the empirical analysis. For all three measures of skill specialisation (*Gini*, *HHI*, and *CV*), OLS regression results indicate that the degree of skill specialisation has a positive effect on earnings (see Table 3). The coefficients of *HHI*, *CV*, and *Gini* are significant at the 1%-level. Players who performed fewer tasks in their careers and thus have accumulated relatively higher levels of task-specific human capital receive

Table 4: The impact of task-specific skill specialisation on salary by main position: OLS regression results

	(4)		(5)		(6)	
Age	0.2300***	(8.00)	0.2300***	(8.00)	0.2314***	(8.06)
Age Squared	-0.0046***	(-8.57)	-0.0046***	(-8.58)	-0.0046***	(-8.63)
Total National Matches	0.0029***	(6.52)	0.0029***	(6.52)	0.0028***	(6.49)
Total Club Matches	0.0014***	(8.94)	0.0014***	(8.96)	0.0014***	(8.93)
Performance	1.3742***	(13.57)	1.3742***	(13.59)	1.3746***	(13.64)
Season Matches Starter	0.0235***	(19.32)	0.0235***	(19.33)	0.0235***	(19.33)
Season Matches Substitute	0.0057**	(2.19)	0.0057**	(2.19)	0.0059**	(2.23)
Left Footed	0.0313*	(1.65)	0.0307	(1.62)	0.0281	(1.49)
Two Footed	0.0457**	(2.18)	0.0464**	(2.21)	0.0455**	(2.16)
Last Season 2. Bundesliga	-0.4856***	(-13.49)	-0.4854***	(-13.48)	-0.4847***	(-13.42)
Midfielder	0.2980***	(5.50)	0.4046***	(4.74)	1.0222***	(3.88)
Forward	0.3672***	(5.80)	0.3887***	(4.01)	0.6012*	(1.96)
HHI	0.1667***	(3.98)				
HHI * Midfielder	-0.1703***	(-3.42)				
HHI * Forward	-0.0328	(-0.58)				
CV			0.2738***	(3.96)		
CV * Midfielder			-0.2770***	(-3.37)		
CV * Forward			-0.0546	(-0.59)		
Gini					0.8961***	(3.87)
Gini * Midfielder					-0.8949***	(-3.41)
Gini * Forward					-0.2684	(-0.88)
Constant	9.0818***	(22.93)	8.9768***	(22.52)	8.3382***	(18.67)
Observations	2002		2002		2002	
R^2	0.700		0.700		0.699	

Notes: Club- and season fixed effects estimation with robust standard errors. The dependent variable is log of annual salary. *t*-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

a salary premium, even when controlling for other effects, such as specific abilities or performance.

The interactions between skill specialisation and main position (defender, midfielder, and forward) provides additional insights (see Table 4). As defenders are the base category, the respective metric of skill specialisation measures the effect for defenders. In Model 4, e.g., the positive and significant coefficient of *HHI* indicates that defenders that are more specialised than the average player on this main position receive higher salaries. This result remains robust across all three metrics. Thus, the statistically not significant interaction *HHI * Forward* indicates that there is no difference between defenders and forwards, i.e. also the latter receive a salary premium on skill specialisation.[19] The same result is obtained for *Gini* and *CV*.

There is, however, a difference of the effect in the case of midfielders, as the interaction term *HHI * Midfielder* is negative and statistically significant (Model 4). The same result is obtained in the models with *Gini* and *CV* (Models 5 and 6). The effect of skill specialisation for midfielders can be computed by summing up the coefficient of *HHI * Midfielder* the coefficient of the reference group (*HHI*), which yields $0.1667 - 0.1703 = -0.0036$. When *Gini* or *CV* are used, the impact of skill specialisation on remunerations of midfielders is also close to zero. This indicates that, compared to defenders and forwards, there is no effect of skill specialisation

[19] H_0 : $HHI + HHI * Forward = 0$ is rejected at the 1%-level.

on midfielders' salaries. Testing the effect of skill specialisation on midfielders' remuneration supports this finding, i.e. the coefficients of the base group's specialisation and the interaction with midfielders are jointly not significantly different from zero.[20] This finding is further supported by estimates of OLS regressions performed for each main position seperately (not reported here). While there is a positive and significant effect of specialisation for defenders and forwards, the effect is not significantly different from zero for midfielders.

4.2. QR Estimates

Tables 5 and 6 report the estimation results using *HHI* as a measure of skill specialisation for the base model and the specification with *HHI* by main position. The results for the alternative measures of skill specialisation, *Gini* and *CV*, can be found in Appendix A (Tables 7, 8, 9, and 10). For all QR model specifications, the results concerning player experience (*Age*, *Age Squared*, *Total National Matches*, *Total Club Matches*) as well as appearances in the starting line-up in the previous season (*Season Matches Starter*) are qualitatively identical across quantiles and support the OLS estimates presented above. Thus, the discussion of the QR results will focus on additional insights compared to the OLS estimates and starts with control variables.

Across the models and specifications, the results show that the effect of two-footedness is not significant across all quantiles. Based on the respective specification, the coefficient of two-footedness is often only (weakly) significant for at most one of the estimated five quantiles of the log salary distribution. As reported in Table 6 for the case of *HHI* interacted with main position, two-footedness has a positive and significant effect on remuneration for players at median of the conditional distribution. An explanation for the weaker impact compared to the results of Bryson et al. (2013) could be the inclusion of a measure for skill versatility. The authors argue that an indirect effect of two-footedness on remuneration is its effect on players' variability, which could be captured by *HHI*, *Gini*, and *CV*, respectively.

The QR estimates reveal further insights on the effect of the number of matches a player started as a back-up and was substituted in during the match (*Season Matches Substitute*). In the OLS regressions the effect of this variable was positive and significant, but notably smaller than the effect of *Season Matches Starter*. The QR estimates reveal that the effect varies notably across quantiles. For players at the lower end of the conditional salary distribution, the number of matches the player was substituted in has a positive return. In contrast, salaries of players in the remainder of the conditional salary distribution are not affected. In sum specifications, the effect is even negative in the upper tail of the conditional salary distribution. An intuition for this result could be that players at the lower end of the conditional salary distribution, i.e. players that are low-paid given their number of substitutions into matches, are mainly back-ups with lower abilities. In their case, the number of matches they are actually substituted in mean that their contribution to team production increases and thus yields a salary premium.

I now turn to the discussion of the impact of skill specialisation across salary quantiles.

[20] H_0 : *HHI* + *HHI* * *Midfielder* = 0 cannot be rejected ($p = 0.9$). The same result is obtained for *Gini* and *CV*.

Table 5: The impact of task-specific skill specialisation on salary: QR results (HHI)

	q10	q25	q50	q75	q90
Age	0.3182***	0.2282***	0.1547***	0.1336***	0.1363***
	(5.81)	(5.28)	(3.75)	(4.43)	(3.77)
Age Squared	-0.0062***	-0.0046***	-0.0031***	-0.0028***	-0.0029***
	(-6.16)	(-5.57)	(-4.09)	(-4.97)	(-4.27)
Total National Matches	0.0030***	0.0022***	0.0022***	0.0023***	0.0026***
	(4.71)	(4.10)	(4.04)	(3.97)	(3.51)
Total Club Matches	0.0010***	0.0013***	0.0014***	0.0013***	0.0014***
	(3.65)	(5.16)	(6.45)	(7.02)	(4.83)
Performance	1.7105***	1.6574***	1.5710***	1.3871***	1.2528***
	(10.95)	(11.69)	(14.11)	(13.88)	(8.78)
Season Matches Starter	0.0309***	0.0272***	0.0218***	0.0179***	0.0147***
	(17.10)	(14.75)	(13.86)	(12.38)	(6.59)
Season Matches Substitute	0.0136***	0.0098**	0.0052	-0.0003	-0.0075
	(3.21)	(2.32)	(1.55)	(-0.12)	(-1.45)
Left Footed	0.0473	0.0194	0.0180	-0.0072	-0.0146
	(1.54)	(0.71)	(0.78)	(-0.29)	(-0.40)
Two Footed	0.0620	0.0440	0.0368	0.0214	0.0094
	(1.59)	(1.50)	(1.49)	(0.85)	(0.26)
Last Season 2. Bundesliga	-0.5143***	-0.5335***	-0.4742***	-0.3806***	-0.3476***
	(-5.72)	(-10.58)	(-10.26)	(-7.87)	(-5.02)
Midfielder	0.0809**	0.1144***	0.1254***	0.1503***	0.1845***
	(2.41)	(4.27)	(5.47)	(7.40)	(5.96)
Forward	0.2861***	0.3143***	0.3593***	0.3840***	0.3761***
	(6.17)	(8.61)	(12.98)	(12.77)	(9.47)
HHI	0.0741**	0.0983***	0.0621**	0.0525**	0.0606*
	(2.07)	(3.36)	(2.39)	(2.09)	(1.75)
Constant	7.1241***	8.5824***	9.9495***	10.8372***	11.1926***
	(9.26)	(14.98)	(17.41)	(26.33)	(22.61)
Pseudo R^2	0.4770	0.4546	0.4589	0.4950	0.5193

Notes: Simultaneous quantile regressions with club- and season fixed effects. $N = 2002$. The dependent variable is log of annual salary. The t-statistics in parentheses are computed using bootstrapped standard errors with 250 repetitions. * p<0.10, ** p<0.05, *** p<0.01.

The results of the base specification, i.e. the models without interaction with main positions, support the OLS regression results, i.e. returns to skill specialisation. Both *HHI* and *CV* have a statistically significant positive effect on remuneration across all quantiles. With the exception of the 0.9 quantile in the model with *HHI* (Table 5) and the 0.1. quantile in the model with *CV* (Table 8 in Appendix A) the effect of the skill specialisation on remuneration is significant at the 5%- or 1%-level. The effect of *Gini* log salaries is also positive across the conditional salary distribution, however, at lower significance levels (Table 7 in Appendix A).

Figure 3 illustrates the core QR results of the main specifications, i.e. the models with measures of task-specific skill specialisation by main position.[21] The shaded area around the line connecting the coefficient estimates for the respective quantile represents a 90% confidence band. Thus, when the band does not include zero, the coefficient is significant. The respective OLS estimates are represented by the black horizontal lines, as they do not change at different

[21]The full regression results can be found in Tables 6 as well as Tables 9 and 10 in Appendix A.

Table 6: The impact of task-specific skill specialisation on salary by main position: QR results (HHI)

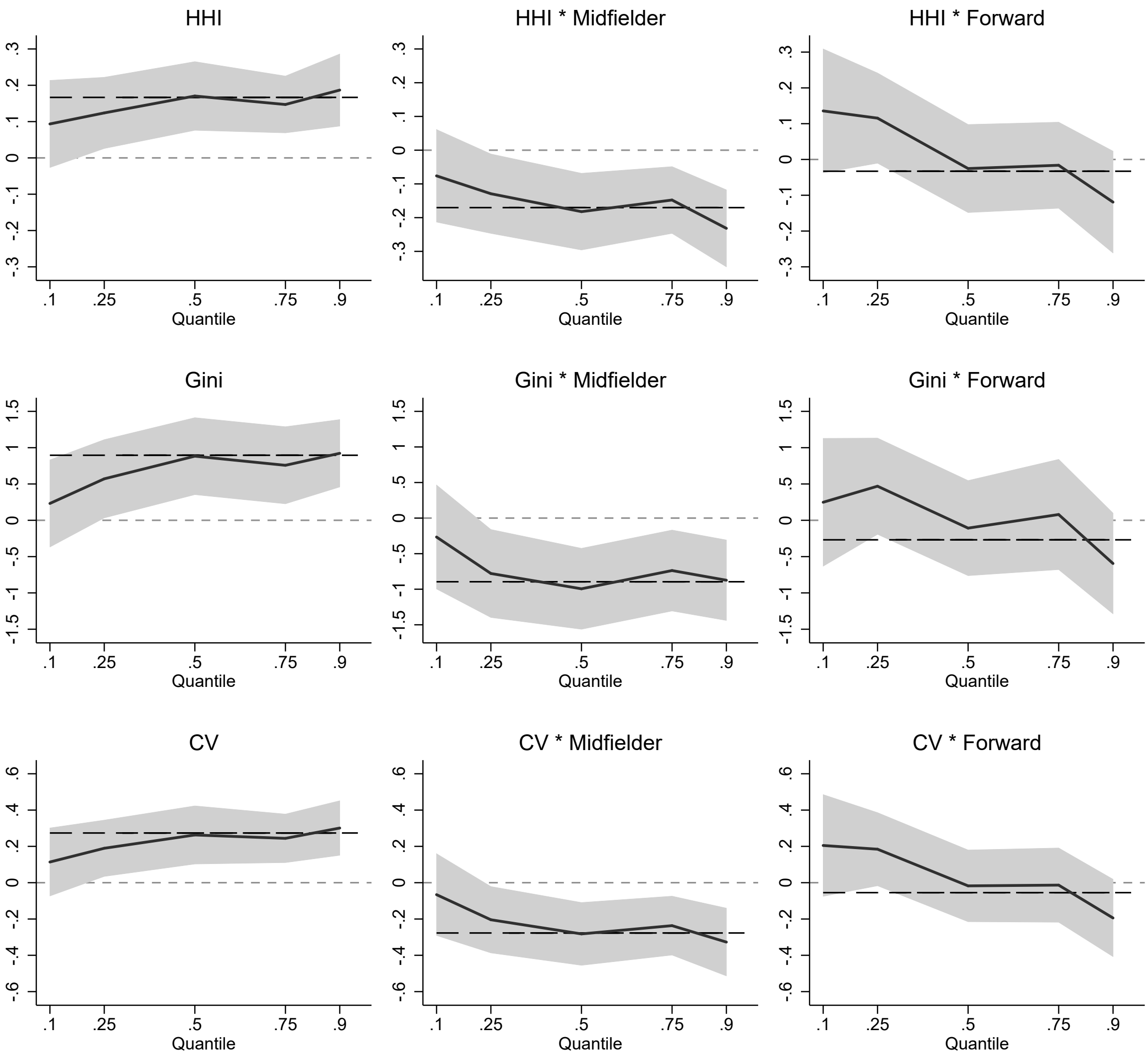
	q10	q25	q50	q75	q90
Age	0.3291***	0.2224***	0.1455***	0.1245***	0.1364***
	(6.21)	(5.15)	(3.64)	(4.37)	(3.55)
Age Squared	-0.0064***	-0.0045***	-0.0030***	-0.0027***	-0.0029***
	(-6.58)	(-5.45)	(-3.99)	(-4.93)	(-4.08)
Total National Matches	0.0031***	0.0022***	0.0022***	0.0023***	0.0027***
	(4.72)	(4.04)	(3.82)	(3.93)	(3.63)
Total Club Matches	0.0011***	0.0013***	0.0015***	0.0014***	0.0013***
	(3.47)	(5.41)	(8.16)	(8.21)	(5.00)
Performance	1.7291***	1.6354***	1.5623***	1.3732***	1.1976***
	(12.03)	(12.29)	(14.52)	(13.73)	(8.12)
Season Matches Starter	0.0309***	0.0273***	0.0222***	0.0178***	0.0134***
	(18.22)	(15.45)	(14.20)	(13.04)	(7.12)
Season Matches Substitute	0.0153***	0.0070*	0.0047	-0.0018	-0.0075*
	(3.94)	(1.78)	(1.29)	(-0.61)	(-1.67)
Left Footed	0.0346	0.0076	0.0216	-0.0014	0.0065
	(1.15)	(0.29)	(0.92)	(-0.06)	(0.19)
Two Footed	0.0483	0.0382	0.0455*	0.0299	0.0188
	(1.24)	(1.37)	(1.77)	(1.23)	(0.62)
Last Season 2. Bundesliga	-0.5181***	-0.5228***	-0.4658***	-0.4024***	-0.3042***
	(-6.00)	(-12.30)	(-10.28)	(-8.08)	(-4.51)
Midfielder	0.1605*	0.2460***	0.3044***	0.3031***	0.4347***
	(1.76)	(3.20)	(4.46)	(4.80)	(6.03)
Forward	0.1692	0.2140**	0.3720***	0.3989***	0.5216***
	(1.44)	(2.53)	(4.72)	(4.88)	(5.60)
HHI	0.0935	0.1240**	0.1705***	0.1471***	0.1869***
	(1.28)	(2.08)	(2.97)	(3.10)	(3.10)
HHI * Midfielder	-0.0761	-0.1290*	-0.1822***	-0.1477**	-0.2317***
	(-0.91)	(-1.81)	(-2.64)	(-2.46)	(-3.34)
HHI * Forward	0.1357	0.1156	-0.0253	-0.0161	-0.1191
	(1.29)	(1.51)	(-0.34)	(-0.22)	(-1.38)
Constant	6.9189***	8.6702***	9.9793***	10.8602***	11.0935***
	(9.20)	(14.60)	(17.58)	(26.72)	(19.85)
Pseudo R^2	0.4784	0.4576	0.4613	0.4975	0.5229

Notes: Simultaneous quantile regressions with club- and season fixed effects. $N = 2002$. The dependent variable is log of annual salary. The t-statistics in parentheses are computed using bootstrapped standard errors with 250 repetitions. * p<0.10, ** p<0.05, *** p<0.01.

levels of the salary distribution. In general, the QR results are similar to the OLS estimates. Defenders receive a salary premium and forwards are not significantly different for defenders. The interaction term of skill specialisation and midfielders is negative.

The figure shows different patterns of impacts for defenders, forwards, and midfielders across the salary distribution, which are similar across all three measures (*HHI*, *Gini*, and *CV*). Overall, the effect of skill specialisation or versatility does not have a statistically significant impact for players that are at the very end of the conditional salary distribution's lower tail. The effect is not statistically significant for the 0.1 quantile for all specifications. For defenders, there seems to be a modest increase of the impact of specialisation on remuneration going from the lowest to the highest point of the conditional salary distribution (three panels on the left in the figure). Relative to defenders, an opposite pattern can be observed for forwards, i.e. the impact

Figure 3: Quantile regression coefficients of the measures on skill specialisation (*HHI*, *Gini*, and *CV*) and their interaction terms with main positions. The horizontal dashed black line is the respective OLS estimate. The shaded area represents a 90% confidence band.



of specialising on fewer tasks decreases along the conditional salary distribution (at least form the 0.25 quantile onwards), as can be seen in the three panels on the right in the figure. The latter effect, however, is not significant for any point of this distribution, which supports the OLS result that there is no statistically significant difference between defenders and forwards.

As in the OLS regressions, midfielders differ from the other two main positions (three panels in the middle column of Figure 3). For all quantiles above 0.1, the estimated coefficients of the interaction between skill specialisation and midfielders are statistically significant and negative and thus indicate that the impact of task-specific skill specialisation on remuneration is significantly lower for midfielders compared to defenders. This negative impact seems to increase for the upper end of the conditional salary distribution, i.e. the 0.9 quantile. Again, the effect of skill specialisation for midfielders can be computed by summing up the coefficient of the interaction between the midfielder dummy and the measure of skill specialisation with the coefficient of the latter for the reference group (defenders). As in the OLS regression, the effect of skill specialisation on remuneration is close to zero for midfielders. Using *Gini* or *CV* yields a similar result, which indicates that midfielders neither benefit from skill specialisation nor from being generalists. Overall, Figure 3 shows interesting patterns across the conditional salary distribution for the coefficients. These differences across quantiles should, however, not be over-interpreted. As almost all estimates lie within the respective confidants bands, the differences among these respective QR estimates and between these QR estimates and the OLS estimates are not statistically significant (Leeds, 2014).

4.3. Robustness Checks

As a robustness check, I performed all estimates analysed above with measures of skill specialisation / versatility without the position adjustment, i.e. *HHI (Absolute)*, *Gini (Absolute)*, and *CV (Absolute)*. The measures used above were adjusted by the respective main positions mean for every season due to the observed differences between the means of the specialisation measures across main positions, i.e. defenders and forwards are, on average, rather specialised, while midfielders are more versatile (See Figure 2). The measures used for robustness checks describe the players's absolute degree of specialisation. All tables with estimation results are provided in Appendix B.

The OLS estimates for all three metrics are in line with the results above. When not differentiating between player types, increased task-specific specialisation yields positive returns. Including interactions with main positions shows that defenders and forwards receive salary premiums on specialisation, while there is no effect of skill specialisation or versatility of midfielders' remunerations. As in the case of position adjusted measures of skill specialisation, all results are highly significant. This result is also supported when OLS regressions are estimated separately for the main positions (not reported). For defenders and forwards, there is a positive and significant impact of skill specialisation on remuneration, while the effect is statistically not different from zero for midfielders. Similar to the OLS estimates, the QR estimates based on the non-adjusted specialisation measures are very similar to those with position adjustment.

5. Discussion and Conclusion

This paper provides new evidence on the impact of skill variety on remuneration of employees. In contrast to previous studies, which focus on occupation- or industry specific human capital, cognitive abilities, or higher education, this paper is a first contribution using a measure of skill specialisation that is based on task-specific human capital. Furthermore, it is one of the first studies that investigates returns to specialisation versus versatility in a professional sports setting, namely the German *Bundesliga*. This setting allows to control for employees' actual performance and specific abilities, which is very difficult, when using data from other labour markets. Of course, the findings in this paper are limited in their generalisability, as they are derived from a professional sports setting that has unique attributes. Football teams can be compared to workplace teams, whose clearly defined members work interdependently within a larger organisation (Katz, 2001). These teams can be characterised as performance teams producing the primary product of the organisation or firm and this production is the primary task of the team members (Crown, 2000). Thus, the findings of the impact of skill specialisation on remuneration are generalisable to employees that work in teams that are involved with the production of any firm's or organisation's output. In turn, they seem inappropriate to describe other types of employees as (top) management or types of service staff not involved in production (Wolfe et al., 2005).

In the analysis, I use the number of matches a player has played on each of the tactical positions in association football as a measure of the accumulated task-specific human capital, i.e. the skill to perform this task. Based on this information, three different measures of skill variety are computed for each player: the HHI, a Gini Coeffient, and a Coefficient of Variation. As the base model, I analyse the relationship without differentiating between occupations, i.e. main field positions (defender, midfielder, forward) in this setting. OLS results indicate a salary premium from specialisation. These results, however, are only partly supported by QR estimates. Overall, this finding of returns from specialisation is in line with previous empirical studies using different measures of skill variety (Aldén et al., 2017; Åstebro and Thompson, 2011; Simmons and Berri, 2009). Considering the applicability of this study's setting to other labour market contexts, it is also not surprising that my findings indicate no returns to generalisation. Most of the previous evidence for returns on skill versatility was found for CEOs and CFOs (Custódio et al., 2013; Datta and Iskandar-Datta, 2014) or university graduates with general major degrees (Artz et al., 2014; Coenen et al., 2015; Leighton and Speer, 2017). CEOs and CFOs are in charge or part of a firm's top management, while a certain fraction of those graduates with tertiary education end up in lower to middle management positions. These have coordinating or supervisory roles rather than direct contributions to firms' outputs and thus naturally require a wider skill set compared to members of production teams.

In a next step of the analysis, I interact the measures of specialisation with the main field position in order to investigate whether there are differences between these occupations. OLS estimates confirm the base results for defenders and forwards, i.e. increased specialisation yields a salary premium. In contrast, the impact of skill specialisation is negligible in the case of midfielders. Thus, compared to defenders and forwards, midfielders receive neither a return on task-specific versatility nor a return on specialisation. This finding is in line with previous studies, which did not find any impact of skill specialisation or versatility on remuneration (Åstebro et al., 2011; Hartog et al., 2010; Parey, 2016).

An explanation for the findings could be that defenders and forwards have more specialised tasks in the football match compared to midfielders. While the latter are almost equally engaged in offensive and defensive plays, the former two groups mainly perform defensive or offensive tasks (Frick, 2007). In addition, this can be seen in the share of tasks performed that are not related to a player's main occupation.[22] On average, a defender plays on defence positions in 89% of all seasonal matches. In the case of forwards, the respective share is almost 95%. Midfielders, however, play only in 67% of all season matches on midfield positions. In the other matches, players whose main occupation is midfielder also perform tasks of defenders of forwards. Thus, they are used more flexibly in team production and seem to be shifted more often between tasks due to, e.g., tactical considerations of team coaches.

An additional intuition behind the results could be the differences in task complexity. While high task complexity benefits specialised employees, employees with versatile skill sets should have a comparative advantage when tasks are less complex (Bublitz and Noseleit, 2014). Anderson (2012) shows that, when problems are difficult to solve, i.e. tasks are difficult, more individuals choose to specialise. Tasks typically performed by defenders and forwards are possibly more specialised / more difficult to learn, while tasks of midfielders do not differ as much. One could argue that the difference between the required abilities / attributes of a centre- versus a left- or right-back (or a centre forward and a left- or right wing) is relatively large. In other words, they require quite specific skills. In contrast, the difference with respect to the requirements of, e.g., defensive-, central-, or attacking midfielders are relatively small. Hence, defenders and forwards should have a higher incentive to specialise, while midfielders should have rather an incentive to become generalists.

Thus, it is not surprising that forwards and defenders earn a premium as specialists. For midfielders, there seems to be a trade-off between skill versatility and specialisation. On the one hand, the relatively large range of comparable tasks and a higher required flexibility provide incentives for a versatile skill set. On the other hand, midfielders also increase their task-specific skills by learning-by-doing. As a task has to be performed several times in order to actually accumulate specific human capital, there is also an incentive for midfielders to focus on fewer tasks. Or in other words, the productivity returns to time spent performing tasks are, in general, greater for employees focussing on fewer tasks (Becker and Murphy, 1992). These opposing effects could be an explanations for why there is no impact on skill versatility on remuneration for midfielders.

Overall, the findings presented in this paper, as well as previous evidence, indicate that employees receive returns to specialisation. For occupations involving a wide range of tasks, however, the positive impact of skill specialisation on remuneration disappears. An explanation could be a trade-off between specialising on certain tasks and skill versatility. Thus, these findings indicate that the impact of specialisation on remuneration is moderated by the characteristics of the occupation. Thus, one direction of future research could be to further investigate how different types of occupations might create comparative advantages for specialists or generalists.

[22]The following shares are based on the sample for the seasons 2010/11 - 2015/16.

A. Appendix: Additional Quantile Regression Results

Table 7: The impact of task-specific skill specialisation on salary: QR results (Gini)

	q10	q25	q50	q75	q90
Age	0.3297***	0.2182***	0.1515***	0.1260***	0.1384***
	(6.16)	(4.76)	(3.90)	(4.24)	(3.70)
Age Squared	-0.0063***	-0.0043***	-0.0031***	-0.0027***	-0.0029***
	(-6.40)	(-4.95)	(-4.20)	(-4.81)	(-4.22)
Total National Matches	0.0028***	0.0021***	0.0020***	0.0021***	0.0024***
	(4.54)	(3.73)	(3.25)	(3.72)	(3.39)
Total Club Matches	0.0010***	0.0012***	0.0013***	0.0014***	0.0015***
	(3.70)	(5.24)	(7.61)	(7.65)	(5.16)
Performance	1.7683***	1.6436***	1.5924***	1.4067***	1.2668***
	(11.66)	(11.60)	(13.32)	(13.68)	(8.57)
Season Matches Starter	0.0311***	0.0273***	0.0220***	0.0178***	0.0147***
	(17.42)	(14.81)	(13.69)	(11.77)	(6.87)
Season Matches Substitute	0.0134***	0.0092**	0.0051	-0.0005	-0.0067
	(3.24)	(2.36)	(1.61)	(-0.18)	(-1.51)
Left Footed	0.0507*	0.0179	0.0155	-0.0148	-0.0130
	(1.89)	(0.63)	(0.74)	(-0.64)	(-0.43)
Two Footed	0.0656	0.0424	0.0355	0.0160	0.0158
	(1.61)	(1.31)	(1.41)	(0.66)	(0.47)
Last Season 2. Bundesliga	-0.5258***	-0.5307***	-0.4704***	-0.3830***	-0.3521***
	(-6.68)	(-12.14)	(-11.03)	(-8.29)	(-5.27)
Midfielder	0.0810**	0.1107***	0.1311***	0.1427***	0.1865***
	(2.52)	(4.16)	(5.94)	(6.77)	(5.99)
Forward	0.2932***	0.3160***	0.3542***	0.3735***	0.3794***
	(6.30)	(9.12)	(13.89)	(12.18)	(10.85)
Gini	0.2217	0.3876**	0.2134*	0.2581*	0.3146*
	(1.46)	(2.56)	(1.88)	(1.93)	(1.90)
Constant	6.7312***	8.4339***	9.8218***	10.7025***	10.8804***
	(9.15)	(13.19)	(18.30)	(25.32)	(19.64)
Pseudo R^2	0.4761	0.4536	0.4580	0.4949	0.5196

Notes: Simultaneous quantile regressions with club- and season fixed effects. N = 2002. The dependent variable is log of annual salary. The t-statistics in parentheses are computed using bootstrapped standard errors with 250 repetitions. * p<0.10, ** p<0.05, *** p<0.01.

Table 8: The impact of task-specific skill specialisation on salary: QR results (CV)

	q10	q25	q50	q75	q90
Age	0.3248***	0.2284***	0.1548***	0.1343***	0.1420***
	(6.11)	(4.87)	(3.88)	(4.40)	(3.70)
Age Squared	-0.0063***	-0.0046***	-0.0031***	-0.0029***	-0.0030***
	(-6.29)	(-5.08)	(-4.17)	(-5.04)	(-4.21)
Total National Matches	0.0029***	0.0022***	0.0021***	0.0024***	0.0025***
	(4.41)	(3.82)	(3.65)	(4.12)	(3.62)
Total Club Matches	0.0010***	0.0013***	0.0014***	0.0014***	0.0015***
	(3.73)	(5.27)	(7.06)	(7.67)	(5.13)
Performance	1.7396***	1.6633***	1.5623***	1.3861***	1.2586***
	(11.17)	(11.46)	(13.67)	(13.22)	(7.76)
Season Matches Starter	0.0308***	0.0269***	0.0219***	0.0177***	0.0148***
	(15.88)	(15.53)	(14.67)	(12.27)	(7.64)
Season Matches Substitute	0.0129***	0.0091**	0.0054	-0.0011	-0.0070
	(3.13)	(2.28)	(1.60)	(-0.40)	(-1.54)
Left Footed	0.0459	0.0202	0.0158	-0.0031	-0.0144
	(1.47)	(0.77)	(0.75)	(-0.13)	(-0.39)
Two Footed	0.0620	0.0481*	0.0377	0.0204	0.0116
	(1.61)	(1.70)	(1.52)	(0.89)	(0.36)
Last Season 2. Bundesliga	-0.5180***	-0.5355***	-0.4750***	-0.3876***	-0.3495***
	(-6.17)	(-13.50)	(-10.35)	(-7.86)	(-4.86)
Midfielder	0.0836***	0.1177***	0.1262***	0.1511***	0.1834***
	(2.65)	(4.37)	(5.40)	(6.92)	(5.57)
Forward	0.2894***	0.3189***	0.3552***	0.3856***	0.3785***
	(6.00)	(7.84)	(12.25)	(14.03)	(11.29)
CV	0.0985*	0.1594***	0.0987***	0.0996**	0.1047**
	(1.81)	(3.55)	(2.68)	(2.30)	(1.99)
Constant	6.9721***	8.5338***	9.9197***	10.7956***	11.0630***
	(9.49)	(13.78)	(18.27)	(25.34)	(19.94)
Pseudo R^2	0.4766	0.4545	0.4588	0.4952	0.5196

Notes: Simultaneous quantile regressions with club- and season fixed effects. N = 2002. The dependent variable is log of annual salary. The t-statistics in parentheses are computed using bootstrapped standard errors with 250 repetitions. * p<0.10, ** p<0.05, *** p<0.01.

Table 9: The impact of task-specific skill specialisation on salary by main position: QR results (Gini)

	q10	q25	q50	q75	q90
Age	0.3174***	0.2079***	0.1481***	0.1257***	0.1377***
	(6.23)	(4.88)	(4.03)	(4.39)	(3.47)
Age Squared	-0.0061***	-0.0042***	-0.0030***	-0.0027***	-0.0029***
	(-6.49)	(-5.15)	(-4.40)	(-4.98)	(-3.97)
Total National Matches	0.0030***	0.0023***	0.0022***	0.0022***	0.0024***
	(4.70)	(4.26)	(3.75)	(3.78)	(3.22)
Total Club Matches	0.0010***	0.0012***	0.0014***	0.0014***	0.0015***
	(3.41)	(5.50)	(7.11)	(7.46)	(5.32)
Performance	1.7572***	1.6303***	1.5736***	1.3818***	1.2252***
	(11.36)	(11.10)	(13.34)	(12.83)	(8.57)
Season Matches Starter	0.0309***	0.0271***	0.0218***	0.0177***	0.0140***
	(17.43)	(16.37)	(14.47)	(14.60)	(7.73)
Season Matches Substitute	0.0143***	0.0067*	0.0038	-0.0022	-0.0071*
	(3.51)	(1.66)	(1.15)	(-0.86)	(-1.70)
Left Footed	0.0437	-0.0016	0.0174	-0.0085	-0.0014
	(1.52)	(-0.05)	(0.79)	(-0.35)	(-0.04)
Two Footed	0.0775*	0.0275	0.0432	0.0300	0.0417
	(1.96)	(0.95)	(1.59)	(1.28)	(1.21)
Last Season 2. Bundesliga	-0.5189***	-0.5061***	-0.4569***	-0.4008***	-0.3109***
	(-6.42)	(-10.87)	(-10.56)	(-8.54)	(-5.05)
Midfielder	0.3475	0.9020**	1.1224***	0.8931**	1.0572***
	(0.78)	(2.37)	(3.25)	(2.56)	(3.08)
Forward	0.0517	-0.1328	0.4635	0.2946	0.9754**
	(0.10)	(-0.33)	(1.15)	(0.63)	(2.28)
Gini	0.2321	0.5714*	0.8832***	0.7577**	0.9229***
	(0.64)	(1.75)	(2.74)	(2.35)	(3.28)
Gini * Midfielder	-0.2659	-0.7787**	-0.9938***	-0.7371**	-0.8732**
	(-0.60)	(-2.07)	(-2.88)	(-2.13)	(-2.54)
Gini * Forward	0.2485	0.4696	-0.1076	0.0801	-0.5945
	(0.46)	(1.17)	(-0.27)	(0.17)	(-1.41)
Constant	6.8951***	8.4352***	9.2423***	10.2338***	10.3443***
	(8.61)	(12.66)	(16.11)	(20.03)	(16.77)
Pseudo R^2	0.4767	0.4569	0.4611	0.4970	0.5223

Notes: Simultaneous quantile regressions with club- and season fixed effects. N = 2002. The dependent variable is log of annual salary. The t-statistics in parentheses are computed using bootstrapped standard errors with 250 repetitions. * p<0.10, ** p<0.05, *** p<0.01.

Table 10: The impact of task-specific skill specialisation on salary by main position: QR results (CV)

	q10	q25	q50	q75	q90
Age	0.3228***	0.2233***	0.1487***	0.1216***	0.1326***
	(5.94)	(5.62)	(4.02)	(4.02)	(3.43)
Age Squared	-0.0062***	-0.0045***	-0.0031***	-0.0026***	-0.0028***
	(-6.22)	(-5.93)	(-4.41)	(-4.59)	(-4.00)
Total National Matches	0.0031***	0.0023***	0.0022***	0.0022***	0.0024***
	(4.88)	(4.45)	(3.80)	(3.71)	(3.07)
Total Club Matches	0.0011***	0.0012***	0.0015***	0.0014***	0.0014***
	(3.38)	(5.44)	(7.42)	(7.25)	(5.08)
Performance	1.7400***	1.6409***	1.5864***	1.3709***	1.1955***
	(10.61)	(11.09)	(13.51)	(12.03)	(8.15)
Season Matches Starter	0.0311***	0.0269***	0.0221***	0.0179***	0.0136***
	(16.71)	(14.90)	(15.07)	(14.44)	(7.26)
Season Matches Substitute	0.0155***	0.0068*	0.0049	-0.0019	-0.0079*
	(3.74)	(1.74)	(1.40)	(-0.67)	(-1.83)
Left Footed	0.0321	0.0063	0.0232	0.0021	0.0100
	(1.06)	(0.23)	(1.02)	(0.08)	(0.29)
Two Footed	0.0497	0.0355	0.0434	0.0311	0.0228
	(1.20)	(1.20)	(1.63)	(1.36)	(0.69)
Last Season 2. Bundesliga	-0.5275***	-0.5254***	-0.4666***	-0.4013***	-0.2955***
	(-6.39)	(-11.73)	(-11.31)	(-8.31)	(-4.47)
Midfielder	0.1457	0.3236***	0.4078***	0.3929***	0.5212***
	(1.06)	(2.80)	(3.91)	(3.91)	(4.62)
Forward	0.0949	0.1529	0.3680***	0.3925***	0.5923***
	(0.55)	(1.18)	(2.90)	(2.95)	(4.38)
CV	0.1141	0.1896**	0.2630***	0.2443***	0.3011***
	(1.00)	(2.02)	(2.71)	(3.01)	(3.30)
CV * Midfielder	-0.0657	-0.2040*	-0.2821***	-0.2364**	-0.3269***
	(-0.48)	(-1.84)	(-2.69)	(-2.40)	(-2.88)
CV * Forward	0.2051	0.1845	-0.0174	-0.0133	-0.1942
	(1.21)	(1.51)	(-0.15)	(-0.11)	(-1.50)
Constant	6.9367***	8.5972***	9.8236***	10.8072***	11.0631***
	(9.31)	(15.73)	(19.23)	(27.35)	(20.11)
Pseudo R^2	0.4776	0.4575	0.4614	0.4976	0.5227

Notes: Simultaneous quantile regressions with club- and season fixed effects. N = 2002. The dependent variable is log of annual salary. The t-statistics in parentheses are computed using bootstrapped standard errors with 250 repetitions. * p<0.10, ** p<0.05, *** p<0.01.

B. Appendix: Robustness Checks

Table 11: The impact of task-specific skill specialisation on salary: OLS regression results

	(R1)		(R2)		(R3)	
Age	0.2346***	(8.17)	0.2347***	(8.18)	0.2359***	(8.22)
Age Squared	-0.0047***	(-8.74)	-0.0047***	(-8.74)	-0.0047***	(-8.76)
Total National Matches	0.0029***	(6.55)	0.0028***	(6.54)	0.0028***	(6.47)
Total Club Matches	0.0014***	(9.02)	0.0014***	(9.00)	0.0014***	(8.90)
Performance	1.3706***	(13.63)	1.3704***	(13.65)	1.3729***	(13.67)
Season Matches Starter	0.0236***	(19.31)	0.0236***	(19.32)	0.0236***	(19.33)
Season Matches Substitute	0.0062**	(2.38)	0.0062**	(2.39)	0.0062**	(2.39)
Left Footed	0.0311	(1.64)	0.0300	(1.58)	0.0278	(1.47)
Two Footed	0.0456**	(2.17)	0.0451**	(2.15)	0.0420**	(2.00)
Last Season 2. Bundesliga	-0.4872***	(-13.46)	-0.4871***	(-13.43)	-0.4866***	(-13.34)
Midfielder	0.1745***	(8.34)	0.1725***	(8.21)	0.1628***	(7.71)
Forward	0.3457***	(13.98)	0.3456***	(13.96)	0.3429***	(13.80)
HHI (Absolute)	0.1575***	(4.35)				
CV (Absolute)			0.0546***	(4.09)		
Gini (Absolute)					0.3824***	(3.12)
Constant	9.0796***	(23.06)	9.0291***	(22.89)	8.8312***	(21.70)
Observations	2002		2002		2002	
R^2	0.699		0.699		0.698	

Notes: Club- and season fixed effects estimation with robust standard errors. The dependent variable is log of annual salary. *t*-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 12: The impact of task-specific skill specialisation on salary by main position: OLS regression results

	(R4)		(R5)		(R6)	
Age	0.2296***	(7.98)	0.2294***	(7.97)	0.2308***	(8.03)
Age Squared	-0.0046***	(-8.55)	-0.0046***	(-8.56)	-0.0046***	(-8.61)
Total National Matches	0.0029***	(6.53)	0.0029***	(6.53)	0.0028***	(6.49)
Total Club Matches	0.0014***	(8.98)	0.0014***	(8.99)	0.0014***	(8.97)
Performance	1.3737***	(13.57)	1.3737***	(13.59)	1.3744***	(13.64)
Season Matches Starter	0.0235***	(19.32)	0.0235***	(19.33)	0.0235***	(19.34)
Season Matches Substitute	0.0058**	(2.20)	0.0058**	(2.20)	0.0059**	(2.24)
Left Footed	0.0316*	(1.67)	0.0309	(1.63)	0.0283	(1.50)
Two Footed	0.0458**	(2.18)	0.0466**	(2.22)	0.0457**	(2.17)
Last Season 2. Bundesliga	-0.4856***	(-13.49)	-0.4855***	(-13.49)	-0.4848***	(-13.43)
Midfielder	0.2954***	(5.45)	0.4005***	(4.69)	1.0171***	(3.84)
Forward	0.3588***	(5.65)	0.3722***	(3.84)	0.5424*	(1.77)
HHI (Absolute)	0.2323***	(3.98)				
HHI (Absolute) * Midfielder	-0.2313***	(-2.66)				
HHI (Absolute) * Forward	-0.0066	(-0.08)				
CV (Absolute)			0.0931***	(3.97)		
CV (Absolute) * Midfielder			-0.0915***	(-2.91)		
CV (Absolute) * Forward			-0.0054	(-0.17)		
Gini (Absolute)					1.0316***	(3.90)
Gini (Absolute) * Midfielder					-1.0087***	(-3.28)
Gini (Absolute) * Forward					-0.2109	(-0.60)
Constant	9.0861***	(22.94)	8.9814***	(22.54)	8.3320***	(18.65)
Observations	2002		2002		2002	
R^2	0.700		0.700		0.700	

Notes: Club- and season fixed effects estimation with robust standard errors. The dependent variable is log of annual salary. *t*-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 13: The impact of task-specific skill specialisation on salary: QR results (HHI)

	q10	q25	q50	q75	q90
Age	0.3061***	0.2249***	0.1504***	0.1310***	0.1338***
	(5.15)	(5.74)	(3.82)	(4.16)	(3.33)
Age Squared	-0.0059***	-0.0045***	-0.0031***	-0.0028***	-0.0029***
	(-5.39)	(-5.98)	(-4.17)	(-4.76)	(-3.85)
Total National Matches	0.0030***	0.0023***	0.0023***	0.0022***	0.0025***
	(4.58)	(4.13)	(3.79)	(3.62)	(3.60)
Total Club Matches	0.0011***	0.0013***	0.0014***	0.0014***	0.0014***
	(3.72)	(5.17)	(7.93)	(8.07)	(5.54)
Performance	1.6926***	1.6009***	1.5920***	1.3782***	1.2625***
	(11.65)	(12.21)	(13.18)	(12.59)	(8.31)
Season Matches Starter	0.0311***	0.0278***	0.0217***	0.0176***	0.0142***
	(16.31)	(16.26)	(14.53)	(12.71)	(7.49)
Season Matches Substitute	0.0138***	0.0099**	0.0051	-0.0019	-0.0070
	(3.36)	(2.31)	(1.48)	(-0.65)	(-1.52)
Left Footed	0.0457	0.0153	0.0182	-0.0003	-0.0085
	(1.35)	(0.58)	(0.79)	(-0.01)	(-0.24)
Two Footed	0.0643	0.0408	0.0404	0.0222	0.0055
	(1.56)	(1.34)	(1.54)	(0.94)	(0.16)
Last Season 2. Bundesliga	-0.5168***	-0.5223***	-0.4690***	-0.3908***	-0.3421***
	(-6.53)	(-11.73)	(-10.47)	(-8.55)	(-5.34)
Midfielder	0.1264***	0.1741***	0.1692***	0.1927***	0.2257***
	(3.28)	(6.54)	(6.87)	(8.10)	(6.82)
Forward	0.3012***	0.3344***	0.3732***	0.3978***	0.4028***
	(6.31)	(8.93)	(12.91)	(13.51)	(11.83)
HHI (Absolute)	0.1570**	0.1975***	0.1543***	0.1392***	0.1417**
	(2.49)	(3.88)	(3.22)	(3.04)	(2.39)
Constant	7.2549***	8.6167***	9.9488***	10.8510***	11.1595***
	(8.93)	(17.13)	(18.54)	(25.15)	(19.91)
Pseudo R^2	0.4776	0.4559	0.4602	0.4961	0.5208

Notes: Simultaneous quantile regressions with club- and season fixed effects. $N = 2002$. The dependent variable is log of annual salary. The t-statistics in parentheses are computed using bootstrapped standard errors with 250 repetitions. * p<0.10, ** p<0.05, *** p<0.01.

Table 14: The impact of task-specific skill specialisation on salary: QR results (Gini)

	q10	q25	q50	q75	q90
Age	0.3296***	0.2147***	0.1538***	0.1275***	0.1367***
	(6.66)	(4.79)	(3.96)	(4.73)	(3.71)
Age Squared	-0.0063***	-0.0043***	-0.0031***	-0.0027***	-0.0029***
	(-6.84)	(-5.00)	(-4.22)	(-5.39)	(-4.28)
Total National Matches	0.0028***	0.0021***	0.0019***	0.0023***	0.0023***
	(4.25)	(4.01)	(3.31)	(3.95)	(3.08)
Total Club Matches	0.0010***	0.0012***	0.0014***	0.0014***	0.0015***
	(3.40)	(4.99)	(7.06)	(7.92)	(5.92)
Performance	1.7596***	1.6538***	1.5843***	1.3858***	1.2465***
	(11.83)	(11.33)	(12.99)	(12.91)	(8.13)
Season Matches Starter	0.0312***	0.0272***	0.0222***	0.0180***	0.0145***
	(16.41)	(14.92)	(14.39)	(12.22)	(7.63)
Season Matches Substitute	0.0132***	0.0094**	0.0060*	-0.0002	-0.0063
	(3.31)	(2.44)	(1.80)	(-0.08)	(-1.52)
Left Footed	0.0502*	0.0230	0.0179	-0.0131	-0.0121
	(1.65)	(0.81)	(0.85)	(-0.54)	(-0.35)
Two Footed	0.0683	0.0444	0.0360	0.0188	0.0256
	(1.64)	(1.42)	(1.41)	(0.78)	(0.80)
Last Season 2. Bundesliga	-0.5227***	-0.5352***	-0.4762***	-0.3802***	-0.3436***
	(-6.21)	(-12.14)	(-10.10)	(-8.81)	(-5.56)
Midfielder	0.1096***	0.1612***	0.1598***	0.1792***	0.2215***
	(3.31)	(6.22)	(6.60)	(7.30)	(7.10)
Forward	0.3061***	0.3353***	0.3611***	0.3814***	0.3918***
	(6.83)	(10.11)	(12.97)	(12.49)	(11.43)
Gini (Absolute)	0.2737	0.5225***	0.3336**	0.3857***	0.4314**
	(1.48)	(2.68)	(2.33)	(2.62)	(2.38)
Constant	6.7165***	8.3965***	9.6960***	10.6226***	10.8672***
	(9.43)	(12.85)	(17.57)	(27.04)	(20.08)
Pseudo R^2	0.4763	0.4763	0.4584	0.4584	0.5202

Notes: Simultaneous quantile regressions with club- and season fixed effects. N = 2002. The dependent variable is log of annual salary. The t-statistics in parentheses are computed using bootstrapped standard errors with 250 repetitions. * p<0.10, ** p<0.05, *** p<0.01.

Table 15: The impact of task-specific skill specialisation on salary: QR results (CV)

	q10	q25	q50	q75	q90
Age	0.3167***	0.2265***	0.1507***	0.1314***	0.1328***
	(5.88)	(5.22)	(3.88)	(4.37)	(3.36)
Age Squared	-0.0061***	-0.0045***	-0.0031***	-0.0028***	-0.0028***
	(-6.21)	(-5.48)	(-4.27)	(-5.04)	(-3.88)
Total National Matches	0.0029***	0.0022***	0.0023***	0.0023***	0.0025***
	(4.80)	(4.09)	(3.99)	(3.91)	(3.48)
Total Club Matches	0.0011***	0.0013***	0.0014***	0.0014***	0.0014***
	(3.71)	(5.25)	(7.03)	(7.86)	(5.43)
Performance	1.7136***	1.6380***	1.5615***	1.3743***	1.2518***
	(11.97)	(12.21)	(13.93)	(12.70)	(8.46)
Season Matches Starter	0.0310***	0.0274***	0.0218***	0.0177***	0.0141***
	(16.69)	(15.90)	(15.22)	(13.47)	(6.90)
Season Matches Substitute	0.0132***	0.0100**	0.0048	-0.0011	-0.0077*
	(3.11)	(2.42)	(1.54)	(-0.45)	(-1.67)
Left Footed	0.0472*	0.0172	0.0162	-0.0003	-0.0087
	(1.76)	(0.64)	(0.75)	(-0.01)	(-0.24)
Two Footed	0.0618	0.0477	0.0423*	0.0174	0.0094
	(1.61)	(1.59)	(1.65)	(0.71)	(0.27)
Last Season 2. Bundesliga	-0.5216***	-0.5349***	-0.4612***	-0.3896***	-0.3423***
	(-5.87)	(-11.76)	(-10.16)	(-8.57)	(-5.21)
Midfielder	0.1177***	0.1701***	0.1690***	0.1915***	0.2294***
	(3.08)	(5.91)	(6.96)	(7.37)	(7.10)
Forward	0.3041***	0.3311***	0.3735***	0.3976***	0.4040***
	(5.80)	(8.66)	(13.89)	(13.13)	(11.44)
CV (Absolute)	0.0442*	0.0689***	0.0517***	0.0497***	0.0524**
	(1.88)	(3.98)	(3.07)	(2.91)	(2.34)
Constant	7.0882***	8.5138***	9.9237***	10.7989***	11.1375***
	(9.56)	(14.57)	(18.81)	(26.04)	(19.75)
Pseudo R^2	0.4770	0.4555	0.4597	0.4960	0.5209

Notes: Simultaneous quantile regressions with club- and season fixed effects. N = 2002. The dependent variable is log of annual salary. The t-statistics in parentheses are computed using bootstrapped standard errors with 250 repetitions. * p<0.10, ** p<0.05, *** p<0.01.

Table 16: The impact of task-specific skill specialisation on salary by main position: QR results (HHI)

	q10	q25	q50	q75	q90
Age	0.3302***	0.2248***	0.1486***	0.1216***	0.1317***
	(5.95)	(5.16)	(3.84)	(4.12)	(3.53)
Age Squared	-0.0064***	-0.0045***	-0.0030***	-0.0026***	-0.0028***
	(-6.26)	(-5.43)	(-4.20)	(-4.69)	(-4.12)
Total National Matches	0.0031***	0.0023***	0.0021***	0.0023***	0.0026***
	(4.62)	(4.10)	(3.57)	(3.90)	(3.56)
Total Club Matches	0.0011***	0.0013***	0.0015***	0.0014***	0.0013***
	(3.71)	(5.64)	(8.00)	(7.62)	(4.92)
Performance	1.7451***	1.6318***	1.5688***	1.3606***	1.2115***
	(11.62)	(11.23)	(13.00)	(12.15)	(8.55)
Season Matches Starter	0.0306***	0.0273***	0.0222***	0.0178***	0.0134***
	(16.69)	(14.95)	(15.48)	(12.97)	(6.63)
Season Matches Substitute	0.0147***	0.0069*	0.0048	-0.0019	-0.0076*
	(3.41)	(1.78)	(1.36)	(-0.66)	(-1.74)
Left Footed	0.0380	0.0074	0.0250	0.0004	0.0119
	(1.22)	(0.27)	(1.12)	(0.02)	(0.38)
Two Footed	0.0408	0.0376	0.0482*	0.0300	0.0172
	(0.97)	(1.32)	(1.86)	(1.25)	(0.54)
Last Season 2. Bundesliga	-0.5137***	-0.5199***	-0.4688***	-0.4084***	-0.2963***
	(-5.79)	(-12.27)	(-11.90)	(-8.41)	(-4.72)
Midfielder	0.1366	0.2445***	0.2991***	0.3028***	0.4313***
	(1.50)	(3.02)	(4.73)	(4.52)	(5.83)
Forward	0.1473	0.2074**	0.3584***	0.3847***	0.5228***
	(1.20)	(2.34)	(4.79)	(5.04)	(5.78)
HHI (Absolute)	0.1111	0.1729**	0.2336***	0.2061***	0.2703***
	(1.18)	(1.96)	(3.16)	(3.13)	(3.30)
HHI (Absolute) * Midfielder	-0.0499	-0.1805	-0.2489**	-0.2026*	-0.3516***
	(-0.33)	(-1.42)	(-2.53)	(-1.96)	(-2.88)
HHI (Absolute) * Forward	0.2504	0.2099*	0.0108	0.0266	-0.1492
	(1.53)	(1.87)	(0.11)	(0.27)	(-1.27)
Constant	6.9366***	8.6406***	9.9273***	10.9115***	11.1527***
	(8.89)	(14.69)	(18.07)	(27.16)	(20.89)
Pseudo R^2	0.4787	0.4579	0.4617	0.4978	0.5231

Notes: Simultaneous quantile regressions with club- and season fixed effects. $N = 2002$. The dependent variable is log of annual salary. The t-statistics in parentheses are computed using bootstrapped standard errors with 250 repetitions. * p<0.10, ** p<0.05, *** p<0.01.

Table 17: The impact of task-specific skill specialisation on salary by main position: QR results (Gini)

	q10	q25	q50	q75	q90
Age	0.3146***	0.2055***	0.1520***	0.1224***	0.1330***
	(5.97)	(4.98)	(4.35)	(4.17)	(3.19)
Age Squared	-0.0060***	-0.0042***	-0.0031***	-0.0026***	-0.0029***
	(-6.21)	(-5.23)	(-4.80)	(-4.77)	(-3.70)
Total National Matches	0.0030***	0.0024***	0.0022***	0.0021***	0.0024***
	(4.24)	(3.99)	(3.70)	(3.75)	(3.19)
Total Club Matches	0.0010***	0.0012***	0.0014***	0.0014***	0.0015***
	(3.22)	(5.25)	(7.83)	(7.35)	(5.61)
Performance	1.7534***	1.6317***	1.5778***	1.3877***	1.2253***
	(11.98)	(11.68)	(13.70)	(12.85)	(8.86)
Season Matches Starter	0.0309***	0.0270***	0.0221***	0.0176***	0.0137***
	(17.50)	(15.68)	(14.41)	(11.95)	(6.81)
Season Matches Substitute	0.0150***	0.0068*	0.0045	-0.0026	-0.0073
	(3.93)	(1.69)	(1.23)	(-0.93)	(-1.63)
Left Footed	0.0446	-0.0014	0.0217	-0.0070	-0.0021
	(1.51)	(-0.05)	(1.04)	(-0.30)	(-0.06)
Two Footed	0.0697*	0.0271	0.0433	0.0265	0.0373
	(1.80)	(1.01)	(1.59)	(1.03)	(1.08)
Last Season 2. Bundesliga	-0.5235***	-0.5081***	-0.4555***	-0.4029***	-0.3117***
	(-6.82)	(-11.41)	(-10.44)	(-8.39)	(-4.49)
Midfielder	0.2430	0.8784**	1.0766***	0.8813***	0.9959***
	(0.56)	(2.28)	(3.18)	(2.67)	(2.87)
Forward	-0.0328	-0.1133	0.4126	0.2360	0.9242**
	(-0.06)	(-0.26)	(1.08)	(0.56)	(2.27)
Gini (Absolute)	0.2413	0.6709*	1.0079***	0.8753**	1.0132***
	(0.58)	(1.85)	(2.84)	(2.55)	(3.05)
Gini (Absolute) * Midfielder	-0.1886	-0.8789**	-1.0870***	-0.8168**	-0.9140**
	(-0.37)	(-1.97)	(-2.74)	(-2.14)	(-2.20)
Gini (Absolute) * Forward	0.3906	0.5578	-0.0312	0.2057	-0.6003
	(0.64)	(1.13)	(-0.07)	(0.43)	(-1.29)
Constant	6.9574***	8.4502***	9.1702***	10.2689***	10.4363***
	(8.65)	(14.01)	(16.26)	(21.59)	(16.60)
Pseudo R^2	0.4769	0.4574	0.4615	0.4974	0.5226

Notes: Simultaneous quantile regressions with club- and season fixed effects. N = 2002. The dependent variable is log of annual salary. The t-statistics in parentheses are computed using bootstrapped standard errors with 250 repetitions. * p<0.10, ** p<0.05, *** p<0.01.

Table 18: The impact of task-specific skill specialisation on salary by main position: QR Results (CV)

	q10	q25	q50	q75	q90
Age	0.3201***	0.2199***	0.1468***	0.1195***	0.1366***
	(5.84)	(5.13)	(3.83)	(3.86)	(3.45)
Age Squared	-0.0062***	-0.0044***	-0.0030***	-0.0026***	-0.0029***
	(-6.08)	(-5.44)	(-4.22)	(-4.47)	(-4.02)
Total National Matches	0.0030***	0.0024***	0.0022***	0.0022***	0.0024***
	(4.69)	(4.26)	(3.62)	(3.94)	(3.24)
Total Club Matches	0.0011***	0.0013***	0.0015***	0.0014***	0.0014***
	(3.61)	(6.11)	(7.82)	(7.93)	(5.26)
Performance	1.7412***	1.6157***	1.5746***	1.3601***	1.1921***
	(11.73)	(11.53)	(13.50)	(12.43)	(8.18)
Season Matches Starter	0.0309***	0.0271***	0.0221***	0.0179***	0.0136***
	(16.21)	(15.83)	(15.54)	(13.30)	(6.75)
Season Matches Substitute	0.0151***	0.0065	0.0045	-0.0019	-0.0086**
	(3.66)	(1.55)	(1.26)	(-0.70)	(-2.06)
Left Footed	0.0335	0.0087	0.0234	-0.0011	0.0077
	(1.07)	(0.31)	(1.03)	(-0.05)	(0.22)
Two Footed	0.0505	0.0371	0.0439*	0.0300	0.0309
	(1.26)	(1.30)	(1.75)	(1.29)	(0.93)
Last Season 2. Bundesliga	-0.5233***	-0.5182***	-0.4656***	-0.4076***	-0.2962***
	(-6.41)	(-11.74)	(-11.63)	(-9.34)	(-4.43)
Midfielder	0.1084	0.3239***	0.4089***	0.4043***	0.5099***
	(0.75)	(2.73)	(4.04)	(3.82)	(4.44)
Forward	0.0510	0.1570	0.3351***	0.3815***	0.5938***
	(0.28)	(1.32)	(2.85)	(2.90)	(4.71)
CV (Absolute)	0.0318	0.0634**	0.0882***	0.0850***	0.1085***
	(0.81)	(2.10)	(3.08)	(3.23)	(3.45)
CV (Absolute) * Midfielder	-0.0030	-0.0701	-0.0973***	-0.0830**	-0.1067**
	(-0.06)	(-1.59)	(-2.59)	(-2.10)	(-2.41)
CV (Absolute) * Forward	0.0950	0.0718*	0.0136	0.0087	-0.0621
	(1.47)	(1.71)	(0.35)	(0.20)	(-1.45)
Constant	7.0032***	8.6558***	9.8626***	10.8335***	10.9949***
	(9.31)	(15.52)	(18.42)	(24.97)	(19.34)
Pseudo R^2	0.4780	0.4580	0.4618	0.4980	0.5230

Notes: Simultaneous quantile regressions with club- and season fixed effects. $N = 2002$. The dependent variable is log of annual salary. The t-statistics in parentheses are computed using bootstrapped standard errors with 250 repetitions. * p<0.10, ** p<0.05, *** p<0.01.

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Affidavit

Ich erkläre hiermit, dass ich die vorgelegten und nachfolgend aufgelisteten Aufsätze selbstständig und nur mit den Hilfen angefertigt habe, die im jeweiligen Aufsatz angegeben oder zusätzlich in der nachfolgenden Liste aufgeführt sind. In der Zusammenarbeit mit den angeführten Koautoren war ich mindestens anteilig beteiligt. Bei den von mir durchgeführten und in den Aufsätzen erwähnten Untersuchungen habe ich die Grundsätze guter wissenschaftlicher Praxis, wie sie in der Satzung der Justus-Liebig-Universität Gießen zur Sicherung guter wissenschaftlicher Praxis niedergelegt sind, eingehalten.

Karol Kempa
Gießen, den 19. April 2018

Submitted Papers:

1. Kempa, Karol and Ulf Moslener (2017), "Climate Policy with the Chequebook – An Economic Analysis of Climate Investment Support", *Economics of Energy & Environmental Policy* 6(1), 111-129.

2. Haas, Christian and Karol Kempa (2018), "Directed Technical Change and Energy Intensity Dynamics: Structural Change vs. Energy Efficiency", *Energy Journal* 39(4), 127-151.

3. Kempa, Karol and Hannes Rusch (2018), "Misconduct and Leader Behaviour in Contests – New Evidence from European Football", *MAGKS Joint Discussion Paper Series No. 29-2016*, University of Marburg.

4. Kempa, Karol (2018), "Generalists vs. Specialists: Skill Variety and Remuneration in Football", mimeo.