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Directed Technical Change and Renewable Energies: Policy Incentives to Promote Solar Innovations

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The Swedish Agency for Growth Policy Analysis
Studentplan 3, S-831 40 Östersund
Phone: +46 10 447 44 00
E-mail: info@tillvaxtanalys.se
www.tillvaxtanalys.se
Contact: Eva Alfredsson
Phone: 010 447 44 31
E-mail: eva.alfredsson@tillvaxtanalys.se

Directed Technical Change and Renewable Energies: Policy Incentives to Promote Solar Innovations

Christopher F. Baum (Boston College)

Hans Lööf (Royal Institute of Technology, Stockholm, UEH Ho Chi Minh City)

Andreas Stephan (Linnaeus University, Växjö)

Ingrid Viklund-Ros (Swedish Public Employment Service, Stockholm)

Abstract

This paper examines determinants of directed technical change at the firm level in the electricity generation industry. We investigate the combined effect of different policy incentives to promote solar innovations. We study the impact of electricity prices, R&D subsidies, public direct investments, feed-in tariffs, and other financial support, as well as possible offsetting effects of public support to wind and fossil- fuel energy technologies for firms in 12 European countries. In total, we consider about 7,000 patents for more than 2,000 firms over the period 1980–2015. The empirical analysis is conducted on both firms specialized in only solar energy technology and firms innovating in two or more technologies. The results provide robust evidence on induced technical change. The effects of public policy are technologically significant.

Keywords: Directed technical change; renewable technologies; induced innovation; panel data; correlated random effects

JEL: C23; O31; O33; Q42; Q55

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Introduction

The ability to achieve sizeable greenhouse-gas emissions reductions to address climate change without compromising future economic growth is linked to the deployment and development of clean technologies, and the energy sector is key in this respect. Europe has a leading role in combating climate change; the European Commission sees technological innovation and R&D in clean energy as important drivers for achieving the objective of climate neutrality by 2050 (European Commission, 2020) and stresses the importance of making policy and market initiatives consistent with the low-carbon pathway.

This paper addresses the question of what we can learn from public interventions in Europe to promote technical change in renewable energy. What are the experiences of various policy initiatives in recent decades? Are the different mechanisms self-reinforcing or competing? Could there be positive spillover effects from fossil-energy technology to renewable technologies?

We construct panel data with micro- and macro-observations from the 12 European countries Austria, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, Great Britain over a 26-year period plus a presample period of 10 years, and estimate how energy prices, public direct investments in renewables, feed-in tariffs, R&D subsidies, financial support to consumers, and spillovers from internal knowledge stocks affect patenting in solar photovoltaic energy. The regression analysis is conducted over the years 1990–2015. In total, we consider about 7,000 patents for 2,100 firms specialising in only solar technology or innovating in two or more energy technologies.

Following Acemoglu, Akcigit, Hanley and Kerr (2016), we compute for each firm the share of patents (related to renewable energy or not) protected in each of the 12 countries. These shares are proxies for how important various markets are for each firm and they are used as weights when computing firm-level variables. The firm-level energy price is computed as a weighted average of country-level electricity prices, and similarly we compute firm-level renewable energy subsidies, energy consumption per capita, GDP per capita, R&D subsidies, public direct investments, feed-in tariffs and public support for customers.

Our paper relates to Noailly and Smeets (2015), who look at directed technical change in the electricity sector in Europe and also rely on the methodology of Acemoglu et al. (2016). Specifically, the authors investigate how fossil fuel prices, market size and knowledge spillovers affect innovation in both renewable energy (including but not separately solar energy) and fossil fuel energy in the electricity sector.

Our analysis is distinguished from the previous paper by focusing more on the effect of different environmental policies rather than on the effect of energy prices, which are at the center of the previous study. To further increase the policy relevance of the paper, contrary to Noailly and Smeets (2015), we investigate competition and complementarity within the energy sector: do subsidies to other renewable and fossil- fuel energies influence innovation in solar photovoltaic energy? This analysis could indicate whether

countries should develop a portfolio of renewables or whether a better strategy is to develop one specific technology.

Overall, we find that energy prices, R&D support, public direct investments, and past knowledge are positively and consistently associated with solar innovations, while no effect from support to consumers can be found. The offsetting effect of public support to other energy technologies is limited or non-existent.

Literature review

An extensive literature in environmental economics studies the factors affecting clean innovation. One branch of this literature can be linked back to Hicks (1932) and the induced innovation hypothesis which states that inventions are initiated by changes in the relative prices of production factors.

The induced innovation hypothesis is a central building block in the endogenous growth model with environmental constraints suggested by Acemoglu, Aghion, Bursz- tyn and Hemous (2012) (AABH). A critical assumption in this model, which allows profit-maximizing firms to decide whether to innovate in environmental technologies, is that carbon-intensive technologies due to path dependence benefit from an initial advantage. Without public intervention to promote clean technology, the transition process towards a carbon-neutral world may be seriously delayed. Therefore, government intervention is necessary and temporary taxes or subsidies can redirect innovation towards the clean sector.

Recently, environmental studies have tested the Hicks hypothesis as well as pre- dictions from the AABH model and related endogenous approaches. Popp (2002), for example, study 11 clean energy-related technologies over the 1970–1994 period and find a positive effect of energy prices on patents, confirming Hicks's predictions. Addressing the issue of crowding out, Popp and Newell (2012) use the patent portfolio of large publicly traded firms from a broad cross-section of industries, including refineries, chemicals, and automobile manufacturers, to test whether an increase in R&D investments in new energy technologies represents additional R&D spending or whether it comes at the expense of other R&D. In line with the AABH model, the authors find that firms tend to increase their investments in new energy technologies when the opportunities become more profitable and reduce other types of innovation.

Building on Acemoglu et al. (2012), Aghion, Dechezleprêtre, Hemous, Martin and Van Reenen (2016) study how carbon taxes and firms' past knowledge stocks induce firms in the automobile sector to invest more in clean (e.g., electric and hybrid) than in dirty (e.g., internal combustion engine) technologies. They find that firms tend to innovate relatively more in clean technologies when they face higher tax-inclusive fuel prices. They also find evidence for path dependence in innovation from both aggregate knowledge spillovers and from the firm's own innovation history.

A main result from Acemoglu et al. (2012) is that when the clean and dirty inputs are strong substitutes, the market size and initial productivity advantage of dirty inputs will direct innovation towards the dirty sector, leading to an environmental disaster. In that case, government intervention is necessary and temporary taxes or subsidies can redirect innovation towards the clean sector.

Noailly and Smeets (2022) list major market failures explaining why firms tend to under-invest in the development of renewable energy (REN) technologies: (i) as in other forms of R&D, due to knowledge externalities firms innovating in REN technologies cannot fully appropriate the returns on their innovation; (ii) in the absence of environmental policy setting a price on carbon emissions, the environmental externality implies that firms have sub-optimal incentives to develop further these low-carbon technologies; (iii)

path dependence in innovation leads technical change to be directed towards fossil-fuel technologies, where most innovation took place historically; and (iv) the prevalence of credit constraints to finance R&D due to factors such as uncertain outcomes of the R&D process, the lack of collateral and information asymmetries be- tween investors and innovating firms (see Hall and Lerner, 2010). This is particularly important for REN technologies since the innovators typically are younger and smaller compared to other firms, and the technology is less mature which may require high irreversible sunk costs. Nelson and Shrimali (2014) estimate that upfront capital costs represent 84–93 percent of total project costs for wind, solar and hydro energy (compared to 66–69 percent for coal and 24–37 percent for gas). Taken together, this means that firms investing in REN technologies are highly dependent on policy support.

Data and empirical strategy

Our data come from the EPO Worldwide Patent Statistical Database (PATSTAT) for patent and patent stock information, the International Renewable Energy Agency (IRENA) for R&D subsidies, the International Energy Agency (IEA) for public direct investments, and the Organisation for Economic Co-operation and Development (OECD) for feed-in tariffs.

We use granted biadic patents as our measure of innovation, assuming that it is important if it has been applied in at least two countries.[1] Our patent data are retrieved from PATSTAT, which indicates, for each of the patents in our sample, if and in which countries it has been validated. Similar to Johnstone, Hašcˇicˇ and Popp (2010); Lanzi, Verdolini and Hašcˇicˇ (2011); Noailly and Smeets (2015), we use International Patent Classification (IPC) codes to identify patents in energy generation. Renewable technology classes are aimed at creating and improving the generation of renewable energy. Using the unique firm identifier, we are able to match firm-level patents to a set of weighted data on variables that may influence demand and supply of renewable energy technologies.

Similar to Noailly and Smeets (2015), we use the application year of priority patents, as this is closer to the year of the inventive idea than the year in which the patent was granted. We compute the annual count of energy patents per firm as well as firm-specific knowledge stocks in renewable and fossil, which are the accumulated number of patent counts over the period.

Estimating the relationship between patenting and demand and supply sources potentially suffers from a number of econometric challenges. While using the zero-inflated negative binomial as a reference alternative, we address this issue first by introducing fixed effects into the count data model. Since our empirical design is a dynamic model in which innovation is determined by past realizations of patenting activities due to the inclusion of the cumulative patent stock on the right-hand side, the assumption of strict exogeneity is violated. We therefore introduce firms' fixed effects using the presample estimator introduced by Blundell, Griffith and Windmeijer (2002), which is used as an initial condition to proxy for unobserved heterogeneity. We compute the firm's cumulative patent stock in all energy technologies over the pre-sample period (1980–1989) and include it as a control in order to capture individual firms' propensity to patent. We then further consider the issue of omitted variables by using IV–Poisson and the correlated random effects (CRE) approach allowing for unobserved time-invariant heterogeneity (Wooldridge, 2010). We also include a full set of time dummies to control for time-dependent factors common to all firms.

[1] See Henderson and Cockburn (1993) for an alternative definition of important patents; they must be applied in at least two of the three major economic regions.

Formally, we apply the following empirical model:

$$\mathrm{PAT}_{SE,it} = \exp\left(\mathbf{EP}_{i,t-1} + \mathbf{A}_{i,t-1} + \phi\, \mathbf{PP}_{i,t-1} + \psi' \mathbf{X}_{it} + \lambda_t\right) \xi_i + u_{it}, \qquad (1)$$

where $\mathrm{PAT}_{SE,it}$ is the number of patents applied for in the solar industry sector by firm i in year t; $\mathbf{EP}_{i,t-1}$ is a vector of energy prices lagged one period; $\mathbf{A}_{i,t-1}$ is the firm's knowledge stock, which depends on past (firm-specific) innovation; $\mathbf{PP}_{i,t-1}$ is a vector of public policy demand and supply measures; $\mathbf{X}_{it}$ is a vector of controls; λ_t is a set of time dummies; ξ_i are firm-specific effects; and u_{it} is the idiosyncratic error term in the regression. All control variables are lagged by one period (except patent stock and firm specialization) to allow for some delay in patenting activities.

In Table 1 and Table 2, we present the public policy induced factors aimed at stimulate technical change in renewable energies. Table 1 provides demand factors using weight measures for both solar photovoltaic and wind energy. The measures are electricity prices, public direct investments, feed-in tariffs and direct public energy support to consumers. It should be noted that the size of the latter is of small size relative to other policy measures.

Table 2 shows summary statistics for R&D subsidies, as well as patent information for solar, wind, and fossil-fuel energy. Notably, fossil-fuel technologies receive by far the largest amount of R&D subsidies, and this technology also dominates the innovation frequency as measured by both stock and flow.

Methodological considerations

Weighting by patent geography. We weight country-level policy measures by the firm's historical distribution of patent protection across countries, which proxies where the firm expects to capture value and, hence, where policy signals are most salient. While these weights may evolve over time as firms reorient toward favourable regulatory regimes, the long panel reduces short-run volatility, and results remain robust across alternative model specifications. The approach may tilt toward export-oriented firms, which is consistent with the international footprint of leading energy innovators.

Model choice and lags. Patent counts are non-negative, highly skewed, and characterised by a large proportion of zeros. Count-data models (ZINB, Poisson-CRE) are therefore appropriate. The presample estimator (Blundell, Griffith & Windmeijer, 2002) captures dynamic initial conditions and controls for unobserved firm-specific fac- tors influencing patenting propensity. The correlated random-effects (CRE) approach (Wooldridge, 2010) further allows for correlation between firm-specific effects and observed regressors. We employ $t - 1$ lags of the policy variables to ensure temporal precedence between policy exposure and subsequent innovation, while year dummies capture contemporaneous shocks common to all firms.

Addressing endogeneity and unobserved heterogeneity. Estimating the relationship between policy variables and firm-level patenting involves risks of endogeneity arising from simultaneity, reverse causality, and omitted variables. To reduce simultaneity between electricity prices and innovation, we estimate IV–Poisson models and instrument electricity prices with GDP per capita and carbon taxes, following Acemoglu et al. (2016) and Noailly and Smeets (2015). The relevance condition is supported by strong theoretical and empirical evidence that both GDP per capita and carbon taxation influ-

ence national electricity prices through demand intensity, energy mix and regulatory cost structures. Regarding the exclusion restriction, once we control for firm-specific fixed effects (via the presample estimator), year dummies, and the full set of policy variables (including R&D subsidies, direct investments and feed-in tariffs), we expect any remaining direct effect of GDP per capita or carbon taxes on firm-level patenting to be limited once we control for firm-specific effects, year dummies, and the full set of policy variables. Nevertheless, the exclusion restriction cannot be empirically verified and remains a strong assumption.

Our empirical strategy—combining presample controls, lagged regressors, the CRE estimator and year dummies—helps mitigate omitted-variable bias, but cannot eliminate it completely. In particular, unobserved time-varying factors that differ across countries or sectors—such as shifts in industrial strategies, unmeasured changes in regulatory frameworks, or technology-specific shocks—may still affect both policy variables and innovation outcomes. As these factors are not fully captured by our data, the estimated coefficients should be interpreted as robust associations consistent with established theoretical predictions, rather than as fully identified structural causal effects. The IV estimates therefore provide directional evidence but should be viewed with appropriate caution.

Results

The results are presented for the zero-inflated model, Poisson random effects and IV–Poisson using the correlated random effects approach. The latter is our preferred model and the estimates are calculated as marginal effects. The analysis contains three innovations related to the existing literature. First, we include a set of policy-induced demand and supply factors in the model (Table 3). Then we consider possible spillovers from other energy technologies to solar technology (Table 4 and Table 5). Finally, we estimate possible offsets on solar patenting due to public support to and regulations of other energy technologies (Table 6). It should also be noted that the electricity price is a combination of taxes and market forces. A final remark is that we consider the patent stock partly as policy induced.

Table 3 presents baseline results of estimating equation (1) by negative binomial models for the panel of firms with at least one solar patent over the period 1980–2015. These firms may hold patents in other renewable or fossil energy technologies. The dependent variable in every column is the number of solar PV patents. The results are mainly in accordance with previous literature.

Column (1) reports zero-inflated negative binomial estimates including the pre- sample trend in order to capture part of the unobserved firm heterogeneity, column (2) adds control for fixed effects by estimating the Poisson model, and column (3) adds control for endogeneity by estimating the two-step IV–Poisson model using the correlated random effects approach. The model instruments for lagged electricity prices and the instruments are GDP per capita and carbon taxes. All models include year dummies.

The robust finding across the models is that energy prices, R&D subsidies and spillovers from patent stocks are positively associated with innovation, and firm spe- cialisation in only solar technology has a negative association with solar patents. This variable is presumably associated with small and newly established firms, which may explain the sign of the estimate. Somewhat surprisingly, the signs of both feed-in tariffs and financial support to consumers are negative, although only the former is statisti- cally significant. Increased energy consumption has a positive impact on technological development in solar energy.

Table 4 and Table 5 divide the results into demand and supply factors related to solar, wind and fossil energy sources. The point estimates for electricity prices and public direct investments to installations of solar PV are all positive and highly significant across the columns. We do not find spillovers from public direct investment in wind in any of the two random effects models. Solar-weighted feed-in tariffs are negatively associated with solar patenting, and we find none or almost none spillover effect from the wind-weighted feed-in tariff. Consumer support for investments in renewable energy solutions is not a driving force of innovation in solar technology. A possible explanation is that the average size of this policy initiative is small over the period for our analysis. Subsidies to R&D in solar technology are a highly significant determinant of solar innovations, while no positive spillovers can be established for R&D subsidies to the two other energy technologies. Robust evidence is reported for internal spillovers from the patent stock, but only weak or no spillovers from the patent stock of other energy technologies.

Table 6 presents selected offset results using equation (1). First, we see that public investment in wind technology is competing with public investment in solar technology and the sign of the offset estimate is negative. The result is the same for feed-in tariffs using our preferred IV–CRE model. Consumer support to wind has no impact on solar innovation. The bottom part of the table shows mixed and interesting results for R&D subsidies. Fossil fuel accounts for the largest part of public support to energy technologies in our data. The preferred IV model shows a negative and statistically significant impact on solar innovations. The opposite is true for R&D support to wind technology.

Discussion and conclusion

Supply-push instruments emerge as the most effective drivers of solar innovation in our empirical analysis. In particular, R&D subsidies and public direct investments have consistently stronger associations with firm-level patenting activity than demand-pull mechanisms such as consumer support or feed-in tariffs. In our preferred IV–Poisson CRE specification, a one–standard-deviation increase in solar R&D subsidies corresponds to approximately 0.10 additional solar patents per firm-year—a non-trivial effect given the low baseline levels of patenting in many firms. Rising electricity prices also contribute positively to solar patenting, in line with induced-innovation theory originating with Hicks (1932).

Interactions across energy technologies play an important role in shaping innovation outcomes. Our results show that R&D support for fossil-fuel technologies tends to crowd out solar innovation, which is consistent with well-documented patterns of lock- in and path dependence. By contrast, R&D support for wind technology shows limited but occasionally positive associations with solar patenting, suggesting the potential for complementarities across renewable technologies. Taken together, these patterns imply that policy packages that continue to subsidize fossil technologies risk impeding the transition to clean energy, while coordinated and balanced support across renewable sectors may accelerate it.

The broader welfare implications reinforce this conclusion. Our findings align with theoretical predictions from Acemoglu et al. (2012) and Acemoglu et al. (2016), who show that delaying or underweighting policy support for clean innovation generates substantial long-run welfare losses. Their estimates suggest that delaying optimal environmental policy by 50 years results in welfare losses equivalent to a permanent 1.7 percent drop in consumption, and that relying on a carbon tax alone is nearly as costly. Targeted R&D subsidies therefore appear close to first-best instruments for overcoming innovation-market failures, while demand-side incentives may primarily encourage deployment rather than invention.

Despite the strength and consistency of the empirical patterns, several limitations remain. Multiple policies often operate simultaneously—such as carbon taxes, feed- in tariffs, and investment grants—which introduces potential multicollinearity that may obscure individual effects. Our empirical design, which includes year effects, presample controls, correlated random effects, and an IV strategy, mitigates but cannot eliminate these concerns. Future research could benefit from event-study approaches focusing on large, discrete policy changes, as well as analyses of how firms dynamically reorient their patenting geographies in response to changing policy environments.

Appendix

All policy variables are constructed from country-level annual data and transformed into firm-level weighted indices following Acemoglu et al. (2016) and Noailly and Smeets (2015). Country-level R&D subsidy data (in millions of euros, constant 2015 prices) are obtained from the International Renewable Energy Agency (IRENA). For each firm, we compute a weighted average of these national values using the firm's historical patenting distribution across the 12 countries as weights. The resulting variable is thus dimensionless and measures a firm's exposure to national R&D subsidy intensity. In our sample, the standard deviation of the solar R&D subsidy variable is 0.27 (Table 2). Hence, the reported coefficient implies that a one–standard-deviation increase in a firm's exposure to solar R&D subsidies is associated with approximately 0.10 additional solar patents per firm-year.

Table 1 Summary statistics: demand factors

Variable	Mean	Std. Dev.	Min	Max
Electricity prices SP	0.0271	0.310	0	5.548
Electricity prices WI	0.0280	0.367	0	5.865
Public direct invest. SP	0.0220	0.286	0	20
Public direct invest. WI	0.0150	0.432	0	44
Feed-in tariff SP	0.0960	0.928	0	67
Feed-in tariff WI	0.0630	1.399	0	118
Public support (cons.) SP	0.0040	0.056	0	1.333
Public support (cons.) WI	0.0020	0.036	0	1.379

Table 2 Summary statistics: supply factors

Variable	Mean	Std. Dev.	Min	Max
R&D subsidies SP	0.0250	0.266	0	4.268
R&D subsidies WI	0.0130	0.178	0	3.899
R&D subsidies FF	0.0840	0.481	0	5.196
Patent SP	0.0220	0.286	0	20
Patent WI	0.0150	0.432	0	44
Patent FF	0.0670	0.535	0	41
Patent stock SP	0.0960	0.928	0	67
Patent stock WI	0.0630	1.399	0	118
Patent stock FF	0.3820	1.906	0	114

Table 3 Dep. var.: Solar PV patents (baseline)

	ZINB	Poisson RE	IV–Poisson CRE
Electricity price t−1	0.344***	0.303**	0.082***
	[0.059]	[0.146]	[0.011]
Public direct invest. t−1	2.321***	2.568	-0.002
	[0.649]	[1.707]	[0.102]
Feed-in tariff t−1	-0.233***	-0.150	-0.036***
	[0.034]	[0.126]	[0.011]
Financial support t−1	-0.562*	-1.077***	-0.051
	[0.338]	[0.403]	[0.052]
R&D subsidies t−1	1.056***	1.031***	0.097***
	[0.098]	[0.162]	[0.012]
Patent stock	0.157***	0.091***	0.007***
	[0.010]	[0.014]	[0.001]
Specialized firm	-0.289***	-0.303***	-0.025***
	[0.086]	[0.164]	[0.010]
Δ Energy cons./cap. t−1	0.178*	0.561***	0.021***
	[0.070]	[0.018]	[0.011]
Pre-sample & year FE	Included	Included	Included

Table 4 Dep. var.: Solar PV patents — Demand factors

	ZINB	Poisson RE	IV–Poisson CRE
PV Electricity price $_{t-1}$	0.337***	0.311**	0.077***
	[0.060]	[0.152]	[0.010]
PV Public direct invest. $_{t-1}$	2.239***	2.533*	-0.033
	[0.659]	[1.482]	[0.111]
WI Public direct invest. $_{t-1}$	1.488**	0.921	0.072
	[0.752]	[1.227]	[0.069]
PV Feed-in tariff $_{t-1}$	-0.227***	-0.155***	-0.038***
	[0.081]	[0.138]	[0.012]
WI Feed-in tariff $_{t-1}$	0.091	0.289	0.061**
	[0.360]	[0.496]	[0.027]
PV Financial support $_{t-1}$	-0.570	-1.053***	-0.055
	[0.346]	[0.301]	[0.056]
WI Financial support $_{t-1}$	0.058	-0.030	0.068***
	[0.529]	[0.782]	[0.044]

Table 5 Dep. var.: Solar PV patents — Supply factors

	ZINB	Poisson RE	IV–Poisson CRE
PV R&D subsidies t−1	1.072***	1.041***	0.105***
	[0.099]	[0.186]	[0.013]
WI R&D subsidies t−1	-0.414	-0.309***	-0.064**
	[0.358]	[0.329]	[0.027]
FF R&D subsidies t−1	-0.026	-0.088***	-0.007
	[0.061]	[0.243]	[0.009]
SP Patent stock	0.156***	0.091***	0.007***
	[0.010]	[0.014]	[0.001]
WI Patent stock	-0.016	-0.032***	-0.003***
	[0.023]	[0.045]	[0.002]
FF Patent stock	0.020	0.032***	0.004*
	[0.016]	[0.034]	[0.002]

Table 6 Dep. var.: Solar PV patents — Determinants and offset factors

	ZINB	Poisson RE	IV–Poisson CRE
PV Public direct invest. (*WI offset*) $_{t-1}$	-0.747***	-0.918	-0.091**
	[0.199]	[0.955]	[0.038]
PV Feed-in tariff (*WI offset*) $_{t-1}$	-0.061	-0.075	-0.019**
	[0.052]	[0.094]	[0.008]
PV Consumer support (*WI offset*) $_{t-1}$	-0.204	-0.010	0.025
	[0.174]	[0.255]	[0.025]
PV R&D subsidies (*WI offset*) $_{t-1}$	0.189**	0.272	0.044***
	[0.093]	[0.260]	[0.014]
PV R&D subsidies (*FF offset*) $_{t-1}$	0.054	-0.014	-0.019**
	[0.059]	[0.144]	[0.009]

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Swedish Agency for Growth Policy Analysis

The Swedish Agency for Growth Policy Analysis
Studentplan 3, S-831 40 Östersund
Phone: +46 10-447 44 00
E-mail: info@tillvaxtanalys.se
Webb: www.tillvaxtanalys.se