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ABSTRACT

The costs of low-carbon energy fell dramatically over the past decade, leading to rapid growth in its deployment. However, many challenges remain to deploy low-carbon energy at a scale necessary to meet net zero carbon emission targets. If net zero goals are to be met, developing complementary technologies and skills will be a necessary part of the next wave of low-carbon energy innovation. These include both improvements in physical capital, such as smart grids to aid integration of intermittent renewables, and human capital, to develop the skills workers need for a low-carbon economy. We document recent trends in energy innovation and discuss the lessons learnt for policy. We then discuss the potential role for complementary innovation in both physical capital—using smart grids as an example of how policy can help—and human capital, where we show how a task approach to labor informs policy and research on the worker skills needed for the energy transition.

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Introduction

The last two decades have seen massive innovations in how energy is generated and used. Hydraulic fracturing has transformed global oil and natural gas markets, so that natural gas could replace coal as the primary fuel for electricity generation. Solar photovoltaic prices have plummeted, and advances in lithium ion batteries provide promise for both electric vehicles and enhanced energy storage.

Despite these advances, many questions remain. The technological challenges of further reducing greenhouse gas emissions are different than the challenges overcome so far. Limiting global warming to no more than 1.5° Celsius, which would reduce projected climate change impacts, is only possible by achieving zero net carbon emissions by mid-century (IEA, 2021b). Meeting today's most ambitious climate policy goals, such as the European Union's Fit for 55 plan to reduce EU greenhouse gas emissions by fifty-five percent relative to 1990 levels by 2030 or California's goal to rely solely on zero-emission energy sources by 2045, requires replacing vast amounts of fossil fuel energy sources with alternative, carbon-free energy sources. Doing so will require long-term energy storage solutions and smart grid technologies to integrate these intermittent energy sources into the grid (IEA 2021c). A recent report from the International Energy Agency (IEA) highlights the need for rapid innovation:

> "Technologies still currently at the prototype or demonstration phase represent around 35 percent of the cumulative CO2 emissions reductions needed to shift to a sustainable path consistent with net-zero emissions by 2070. For today's early-stage technologies to dominate their sectors by mid-century, we would require more rapid innovation cycles than in recent energy technology history." (IEA 2021c, p.22)

We argue that this new wave of low-carbon innovation requires not only rapid innovation, but different innovation. Reducing the cost of low-carbon energy is not enough. As happened with information and communication technologies (Breshnan et al. 2002) and electrification (Gray

2013), developing complementary technologies and skills is essential to accelerate adoption of low-carbon energy technologies. If net zero goals are to be met, innovation on these complementary technologies and the development of worker skills needed by low-carbon technologies will be a necessary part of the next wave of low-carbon energy innovation.

Most of the literature on a low-carbon energy transition focuses on low-carbon energy substitutes for fossil fuels, such as wind, solar, or electric vehicles (e.g., Johnstone et al. 2010, Aghion et al. 2016). But renewable energy's intermittent nature poses new challenges for grid stability and reliability. As we accelerate the decarbonization transition in the electricity sector, further R&D efforts are needed for developing enabling technologies that enhance the flexibility of electricity systems and enable more renewables integration, as well as enabling increased electrification of the economy, such as a transition to electric vehicles or the production of green hydrogen. Progress on many such enabling technologies lags behind that of wind and solar.

Moreover, a changing energy landscape requires new human capital. We are, in essence, experiencing "technological" change with workers as well, and with few exceptions, such as in the European Green Deal, addressing the impact of the energy transition on workers' reskilling and retraining receives less policy support. Yet changing workforce needs matter for several reasons. First, the acceleration in renewable energy investments poses a significant threat to workers and communities producing fossil fuels. The threats faced by these communities are a barrier to political support for carbon pricing and climate policy in the U.S and elsewhere (Weber 2019, Vona 2019). Second, new employment opportunities in low-carbon energy sectors will require workers with the skills necessary for these jobs (Vona et al. 2018) and the cost of technology adoption depends on the availability of the appropriate skills in the workforce. The vast literature on the labor market impacts of new technologies highlights that certain skills (e.g., abstract and cognitive) are complementary to new technologies, while others (routine and manual) are substituted by them (Autor et al. 2003; Autor 2013). Last, cognitive skills are also a key input of a country's innovative capabilities. Their availability is important to solve the remaining innovation challenges described in the first part of the paper.

This paper explores both dimensions of the energy transition. We begin by documenting recent trends in energy innovation and discussing the lessons learnt for policy. We then discuss the potential role for complementary innovation in both physical capital—using smart grids as an example of how policy can help—and human capital, where we show how a task approach to labor informs policy and research on the worker skills needed for the energy transition.

Recent Trends in Green Innovation: Lessons for Policy

Electricity generation is one of the largest contributors to carbon emissions. In 2020, it was responsible for thirty-six percent of all power-sector emissions (IEA 2021b). Yet, it is also the sector most ready to accelerate progress towards net-zero goals by 2050 (IRENA 2022). The costs of electricity generated from renewable sources fell dramatically since 2010, leading to rapid growth in the use of renewable sources. These cost reductions are partly attributable to technological advances, as described in Table 1. For example, the weighted-average levelized cost of electricity from wind decreased by fifty-six percent to USD 0.039/kWh. The cost of utility-scale solar photovoltaic generation has seen an even more striking decline over the same period – eighty-five percent - also positioning it as cheaper than fossil fuels in some locations.

To illustrate recent innovation trends, Figure 1 presents data on four low-carbon energy technologies: solar photovoltaics (PV), wind, hybrid and electric vehicles, and building energy

Table 1: Contribution of technology to cost reductions

Technology		Reduction in levelized cost (2010-20)	Examples of technological advancements
Solar PV	Utility-scale	85%	- Improvements in wafer cutting techniques, using diamond wire sawing, enabled a reduction in polysilicon usage - Shift from multi-crystalline to mono-crystalline cells reduced chemical impurities and material defects
	Residential	49% - 82%	
	Commercial	50% - 79%	
Concentrating solar power	Solar towers	48%	- Use of molten salt heat transfer fluids and direct steam generation enabled higher temperature and longer thermal energy storage duration
	Parabolic trough collector	69% (2011-2019)	- Improvements in special coatings on the absorber tube and in insulation measures for the receiver have reduced thermal losses
Wind	Onshore	56%	- Increase in rotor diameter - Increase in hub height - Improvements in turbine capacity
	Offshore	48%	
Storage	Lithium-ion cells	98% (1991-2018)	- Improvements in cell energy density - Improvements in energy-to-power ratio (storage duration)

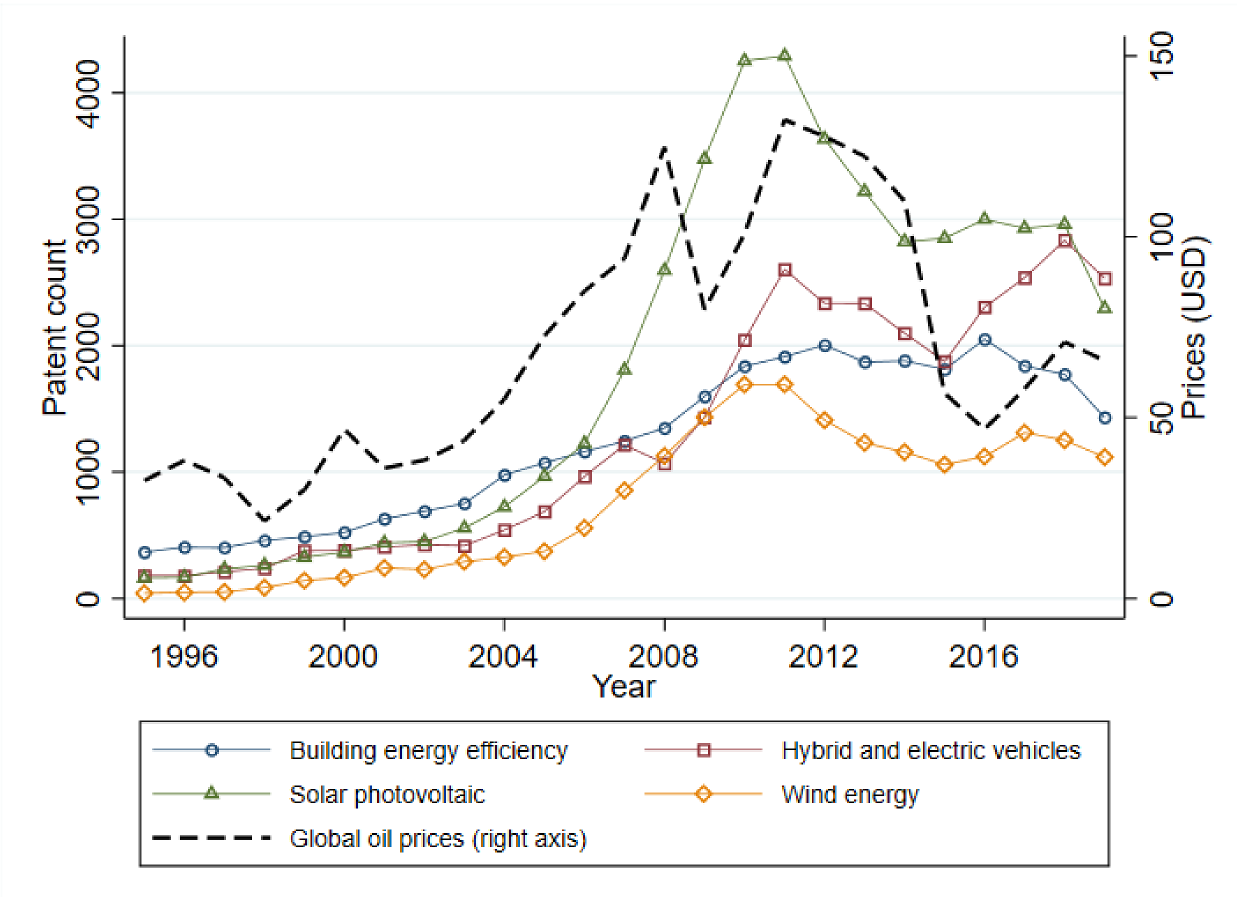
Source: IRENA (2022)

efficiency. Our patent data come from the European Patent Office (EPO) World Patent Statistical Database (PATSTAT), which includes over one hundred million patent applications from ninety patent authorities. To control for patent quality, we only include patent applications filed in two or more patent offices. Inventors must file a patent at each patent office for which they desire protection. Filing in multiple offices is a signal that the patented invention is of higher quality (e.g. Lanjouw et al. 1998, Harhoff et al. 2003).[5] We use the European Patent Office's "Y scheme", which provides separate classifications for technologies pertaining to climate change mitigation

[5] All filings at regional patent offices such as the EPO are included, as these signal intent to seek protection in multiple countries.

and adaptation, to identify relevant patents. These classifications complement standard patent classification schemes such as the Cooperative Patent Classification (CPC) scheme, grouping together relevant technologies that may appear in a wide range of traditional patent classes. Online Appendix A lists the patent classes used to identify each technology.

Figure 1: Global Low-carbon Energy Patents



Notes: Figure shows global counts of energy patents for patents filed in two or more countries. Patents are sorted by priority year. Patent extractions from the EPO World Patent Statistical Database (PATSTAT). Oil price data are $/barrel, in 2022 US dollars, taken from the US Energy Information Administration, Short-Term Energy Outlook, June 2022.

Two notable trends stand out. First, each energy technology experiences dramatic growth in the early 2010s. For most technologies, global patent counts increased by a factor of three or more from 2006 to 2011. Second, this sudden increase in patenting was followed by a rapid decline. The exception is building energy efficiency, which grew less rapidly and plateaued by 2010. Hybrid and electric vehicle patents experience a second growth wave beginning in 2016.

A rich literature has developed to better understand the factors influencing the rapid changes in energy innovation during the past twenty years (Popp 2019). Understanding what roles the private and public sector play is important to develop policy solutions to promote remaining innovation needs. Multiple market failures affect energy innovation, and different technologies are affected in different ways. As such, no one policy instrument is sufficient. Different policies address different market failures and work at different stages of technology development.

Most importantly, demand matters. Innovators focus on products that customers will want. Higher energy prices encourage innovation on alternative energy sources and on some energy efficiency technologies. Both Popp (2002) and Verdolini and Galeotti (2011) estimate a 10 percent increase in energy prices leads to a 3.5 percent increase in alternative energy and energy efficiency patenting. Similarly, when facing higher fuel prices, firms in the automotive industry produce more innovations on clean technologies, such as electric and hybrid cars, and less in fossil-fuel technologies that improve internal combustion engines when facing higher fuel prices (Aghion et al. 2016). A ten percent higher fuel price is associated with about ten percent more low-emission energy patents and seven percent fewer fossil-fuel patents. To show that both the recent increase and decreases in patenting correspond with energy price trends, Figure 1 plots global oil prices on the right axis, using U.S. imported crude oil prices.

However, higher energy prices alone are not sufficient to fully support low-carbon energy innovation. As the prices of wind and solar become competitive with fossil fuels, deployment of these technologies increases. Similarly, higher energy prices encourage more investment in energy efficiency. But these investments also provide social benefits from pollution reductions that are not reflected in market prices without government intervention. As a result, potential demand for low-carbon energy technologies depends on effective environmental policy. Policies addressing the environmental externalities from fossil fuels increase the potential market size for low-carbon energy innovation, and are often referred to as *demand-pull policies*.

The choice of policy tool affects both the pace and direction of innovation. Demand-pull policies to promote low-carbon energy can either be *technology-neutral* or *technology-specific*. Technology-neutral policies provide broad mandates, such as reducing emissions to a certain level but leave it to consumers and firms to decide how to comply. Examples include a carbon tax or cap-and-trade, which targets all emissions equally. British firms exposed to the European Union's Emissions Trading System (EU ETS) increased patenting by twenty to thirty percent relative to similar non-regulated firms (Calel 2020). Weakened regulation, such as falling EU-ETS prices after the Great Recession, may also explain the recent decline in low-carbon energy patenting.

Technology-specific policies stimulate the use of individual technologies. For example, tax credits for electric vehicles or rooftop solar energy are only available to consumers who purchase these products. Because technology-neutral policies promote technologies closest to being competitive in the market without policy support (Johnstone et al. 2010), technology-specific policies play an important role for emerging technologies with higher costs. Before the recent wave of innovation, the price of onshore wind was competitive with fossil fuels, but solar PV was not. As a result, innovation in countries with mandates to provide alternative energy focused on wind. In contrast, innovation in solar PV occurred in countries with technology-specific policies targeting solar energy. Most notably, German feed-in tariffs were over five times higher for solar than for wind (Johnstone et al. 2010). Gerarden (2022) estimates that solar energy subsidies increased demand for solar power by seventy-eight percent between 2010 and 2015, with over half of that increase due to lower costs from innovation induced by the subsidies. While Germany was the leader on subsidies, eighty-six percent of the benefits of cost decreases from the resulting innovation occurred outside Germany, suggesting large spillover benefits. Both studies indicated that while technology-specific policies may raise short-term costs, judicious use of them helps promote the development of low-emission technologies further from the market, such as offshore wind or carbon capture and sequestration.

When choosing technology-specific policies, the consideration of other market failures informs both which technologies to target and which policy instrument to use. Other market failures such as learning-by-doing, path dependency, and capital market failures limit incentives to invest in emerging energy technologies (Acemoglu et al. 2016, Fischer et al. 2017, Lehmann and Söderholm, 2018). Both learning-by-doing and path dependency justify technology-specific deployment policies such as feed-in tariffs or tax credits—most notably when the resulting cost-reductions benefit not only early adopters, but also those who wait to adopt until costs fall (e.g., Lehmann and Söderholm, 2018). However, the existing literature on learning-by-doing generally suggests that the benefits of learning-by-doing are not sufficient to justify current levels of deployment subsidies (e.g., Nemet 2012, Fischer et al. 2017, Tang, 2018). In a cross-country study of energy patenting, Nesta et al. (2018) provide evidence on the importance of path dependency. Policies promoting low-carbon energy innovation are not successful in countries with little existing renewable energy innovation capacity. Command-and-control policies spur low-carbon energy innovation at medium levels of capacity. Beyond a high capacity threshold, however, only market based policies provide incentives for further low-carbon energy innovation. These results reinforce the need to develop the competences, especially the human capital, necessary for green innovation.

In contrast, the evidence on capital market failures provides mixed results. Howell (2017) provides evidence that early financing through the US Department of Energy Small Business Innovation Research (SBIR) program helps overcome capital market failures in low-carbon energy. However, Goldstein et al. (2020) find that receiving an early-stage award from the US Advanced Research Projects Agency-Energy (ARPA-E) does not significantly decrease the probability of exiting compared to comparable but non-participating cleantech startups. Van den Heuvel and Popp (2022) reconcile these results, noting that while financial constraints may be a burden for low-carbon energy startups, providing public funding for low-carbon energy startups does not address demand-side market failures. Increasing demand for low-carbon energy technology is key to promoting the success of low-carbon energy investments.

At the same time, the "public good" nature of knowledge creates *spillovers* that benefit the public as a whole, but not the innovator. Inventors use knowledge created by others as building blocks for their own work. For example, Myers and Lanahan (2022) estimate that DOE SBIR grant recipients capture just twenty-five to fifty percent of the value of patents generated by their R&D, as spillovers from their work generate follow-up innovation by outsiders. Because they do not reap the benefits of these spillovers, potential innovators do less research than would otherwise be desirable, even if environmental policies to address externalities are in place. Science policy to support research performed in both the private and the public sectors helps bridge this gap. Examples include direct government funding of research projects and indirect support such as tax credits for private-sector research and development. Policies supporting technology development directly are often referred to as *technology-push* policies.

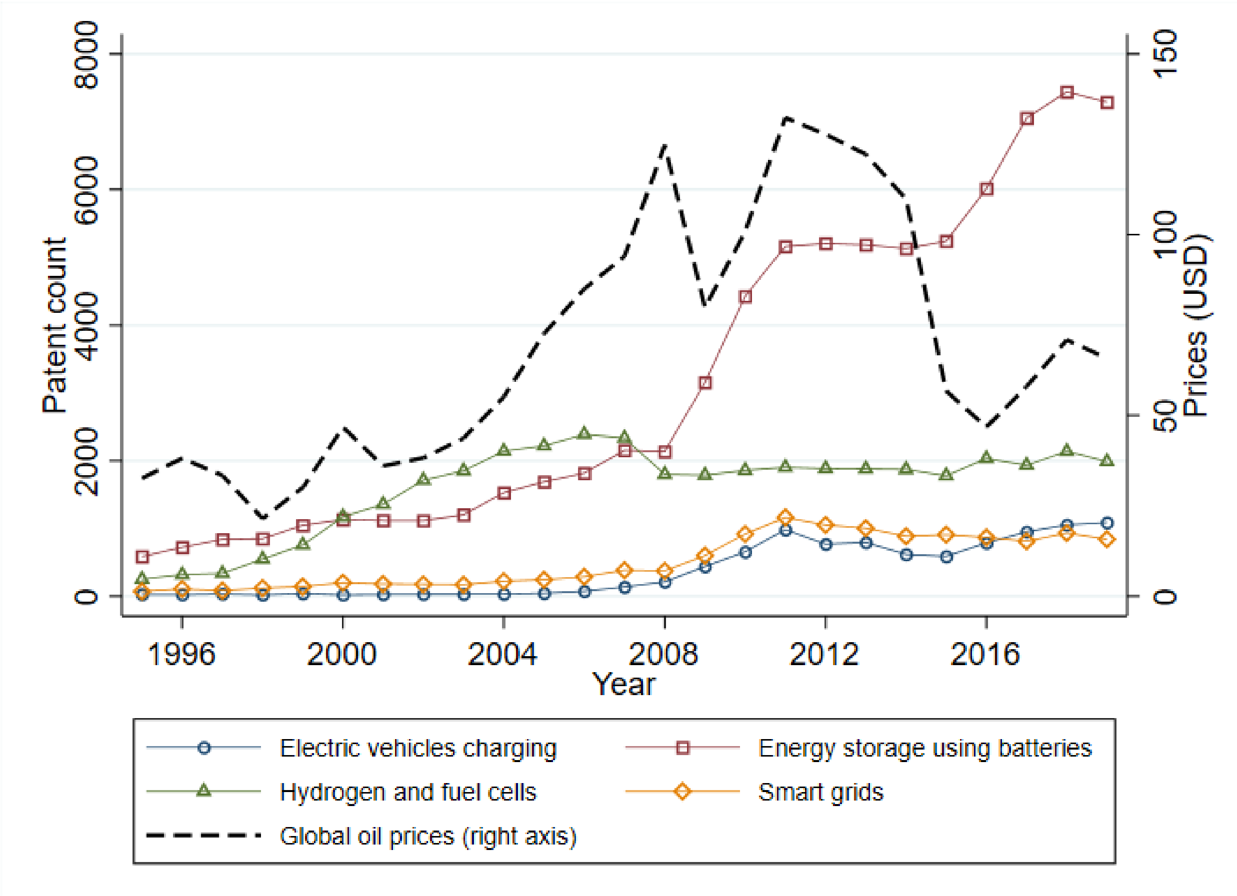
For technology-push polices, government R&D should play a *larger* role for cleaner technologies if spillovers from green innovation are larger than for other technologies. Both

Dechezleprêtre et al. (2017) and Popp and Newell (2012) find that low-carbon energy R&D generates large spillovers, comparable to spillovers in other emerging fields such as IT or nanotechnology. Noailly and Shestalova (2017) find similar results, but only for emerging technologies such as energy storage. Consistent with the notion that government R&D is most important for emerging technologies, Costantini et al. (2015) compare patenting in conventional first-generation biofuels to patenting in more advanced second-generation biofuels. While technology-push policies do not induce innovation for more mature technologies (e.g., first-generation biofuels), they are important for fostering development in emerging, more advanced technologies.

Developing Enabling Energy Technologies

Economists have just begun to explore explanations of the recent fall in patenting (see, e.g., Popp et al. 2022). Whether this decline is problematic depends, in part, on the technology. The dramatic decrease in low-carbon energy prices suggests the wave of innovation in the early 2000s was successful. In fact, by 2017 solar PV costs had fallen below what experts had earlier predicted for the year 2030 (Nemet, 2019)! That electric vehicle patents are increasing again shows that technology is still evolving where challenges remain. However, as wind and solar technologies are deployed at scale, their intermittent nature will pose a new array of challenges for grid stability and reliability. More concerning is that patenting activity also slowed down in technologies that have not yet attained maturity and are critical for achieving decarbonization goals (IEA 2021c). The IEA estimates that half of the technologies needed to achieve net-zero goals by 2050 are still in early stages of development (IEA 2021b). Further R&D efforts are needed to develop technologies that enhance the flexibility of electricity systems and enable further renewables integration. These include technologies to increase electric grid flexibility as well as reduce emissions in transportation and industry. Figure 2 shows patent trends for four such enabling technologies: batteries for energy storage, EV charging, smart grids, and hydrogen energy.

Figure 2: Global Enabling Technology Patents



Notes: Figure shows global counts of energy patents for patents filed in two or more countries. Patents are sorted by priority year. Patent extractions from the EPO World Patent Statistical Database (PATSTAT). Oil price data are $/barrel, in 2022 US dollars, taken from the US Energy Information Administration, Short-Term Energy Outlook, June 2022.

Notably, patenting in batteries for energy storage did not decline after rapid growth in the early 2010s, and is rising once again. However, this trend tracks EV patenting more generally and largely targets batteries for electric vehicles. EV charging patents are also increasing, albeit at a slower pace. In contrast, further R&D efforts are needed to develop technologies that enhance the flexibility of electricity systems and enable further renewables integration. In 2020, there was total of seventeen GW installed storage capacity worldwide in, whereas 148 GW are needed by 2025 to stay on track for achieving net-zero targets by mid-century (IEA 2021b). Because the market for electric vehicle batteries is ten times larger than the market for grid scale batteries, battery innovation steered away from alternative technologies that may be better suited to the needs of stationary power storage, where size and weight are secondary preoccupations (IEA 2021a). Examples of battery technologies that have not achieved the same level of maturity as lithium-ion batteries include flow batteries and lithium iron phosphate batteries. The latter present advantages that would make it a better candidate for grid-scale storage than the nickel manganese cobalt chemistries used in electric vehicle batteries.

Progress towards the development of dispatchable cleaner energy sources is also needed to address hard to decarbonize sectors. Hydrogen energy provides an example that can be used to retrofit existing assets and ease the low-carbon energy transition in the short-to-medium run. “Green” hydrogen produced from renewable electricity could serve as a means of power storage. Both “green” and “blue” hydrogen produced from fossil fuels with carbon capture and storage could become an energy source for hard to decarbonize sectors such as iron and steel or heavy duty transportation (IEA 2019).

The level of patenting in smart-grid innovation has been lower than batteries or hydrogen, and leveled off slightly below its 2011 peak. Smart grids encompass a range of technologies that include—but are not limited to—smart meters, remote and automated sensing, smart switching, hierarchical or distributed control architectures and an array of big data analytics and artificial intelligence applications. Smart grid innovation will be pivotal in supporting the integration of technologies and new business models that enhance flexibility, such as energy storage, vehicle-to-grid applications, and demand-response. A modernized grid would leverage a variety of tools from both the supply and demand sides to achieve flexibility, in contrast with conventional strategies that have relied on controlling power generation. These include demand-side management for peak-shaving, electricity storage, vehicle-to-grid and grid-to-vehicle applications, the geographical and technological diversification of renewables generation and supergrids. Smart grid technologies will be a linchpin in the implementation of these various flexibility tools (Martinot, 2016).

Promoting innovation on enabling technologies faces several challenges. While the costs of wind and solar were falling over the past decade, their primary competition came from fossil fuels. The goals of low-carbon energy policy at that time were clear—to lower costs and bring low-carbon energy to the market as soon as possible. Today low-carbon energy policy operates in a more complicated landscape. In many cases, such as electricity generation, renewable energy may cost less that fossil fuels. But because of both technological and supply constraints, renewable sources can not yet satisfy all our energy needs. Energy policy now operates in a world where policy both promotes expanded use of renewables currently ready for the market while still needing to provide incentives to develop technologies further from the market that will be necessary for full decarbonization. As discussed earlier, no one low-carbon energy technology policy is a silver bullet. Identifying the policies needed at different stages of technological development is important for promoting the development of enabling energy technologies.

Innovation on enabling technologies faces several challenges. Green and blue hydrogen provide a low-carbon energy alternative for heavy industry, but remain costly (IEA 2019). Targeted policies and R&D investment will be needed to bring costs down before these technologies are used at scale. Investments in smart-grid technologies, the integration of intermittent renewable energy technologies into the grid, and the adoption of connected vehicle infrastructure emphasize improvements in public infrastructure. Better management of the grid benefits all users of the grid, including producers of wind and solar energy. Enabling energy technologies, such as smart grids, are both more original (relying on a broader base of existing technologies) and more radical (building on ideas outside their own technological domain) than other technologies (Popp et al. 2022). Technologies such as smart grids enable decentralized energy production, implying organizational innovation as well as technological innovation. These findings all point to potential large spillovers from enabling technologies, so that targeted demand-side policies and R&D subsides both have a role to play.

We use smart grids as an example of the challenges for promoting innovation in enabling energy technologies. The smart grid would leverage digital technologies that enable two-way data sharing. Building a smarter grid implies developing and deploying both hardware and software to collect and utilize highly granular power data in applications that help the grid operate more efficiently (Colak et al. 2016). Because a smart grid is an evolved digitalized network featuring club goods characteristics, its deployment poses additional challenges beyond those experienced in earlier waves of low-carbon energy innovation. First, as more devices connect to the internet, the vulnerability of the grid to cyberattacks will surge, posing risks to data privacy and threatening to engender service disruptions that could cause substantial material losses (Brown et al. 2018). To mitigate these risks, governments and industry have spearheaded standardization initiatives to devise cybersecurity architectures and protocols for devices that exchange sensitive data. New technologies such as blockchains present an array of potential applications to the grid and hold promise for countering cybersecurity threats (Kuzlu et al. 2020). Beyond cybersecurity, the need for grid devices to interconnect in a reliable way may also pose additional challenges to technology development and deployment (Grégoire-Zawilski and Popp, 2022). Consensus around interoperability protocols may provide direction to technology development and mitigate the risks associated with conducting R&D in networked technologies, where changing technology protocols may render devices obsolete. There may be a role for governments and industry to join forces in coordinating the standards development process. In addition, because this sector of technology is fast-moving and smart grid devices generate network externalities, providing subsidies to early adopters who are at heightened risks of stranded assets may be justified.

Grégoire-Zawilski and Popp (2022) analyze the effect of technology standards that coordinate technology development on smart grid innovation. Because it involves developing digital applications to support the distribution and transmission of electricity, smart grid innovation pools expertise from multiple technological domains. Firms that innovate in this space are diverse in terms of age, size and technological backgrounds. Knowledge flows across sectors, requiring firms to internalize innovations from diverse technological spaces and to design products that can work together. Interoperability standards set by national and international standard-setting organizations provide specific technological specifications that a product must meet to conform with the standard. While these standards are voluntary, the networked nature of smart grid innovation supplies incentives for firms to conform with these specifications. For example, standard IEC/TR 61850, developed by the International Electrotechnical Commission, defines protocols for communication between intelligent devices within power utility automation systems, and as such, is crucial to coordinate the deployment of smart grids devices developed by different firms.

Overall, interoperability standards decrease both the likelihood that a firm develops a smart grid patent in a given year (the extensive margin) and how much it patents in that same year (the intensive margin). However, these effects vary by type of inventor. After standards are introduced, large industry incumbents experience a reduction in patenting at both the intensive and extensive margin. Grégoire-Zawilski and Popp (2022) speculate that these firm's inventive activities take place prior to the introduction of standards, so that standardization provides an endorsement of their technology. However, the introduction of standards facilitates the entry of new inventors. Standards provide information and know-how about accepted practices and technical specifications that would otherwise only be available to industry insiders.

Heterogeneous effects over time provides further insights. Introducing standards early in the innovative process facilitates entry, while later standards are associated with a reduction in the intensity of patenting. This pattern is consistent with standards both providing information to inventors (and thus providing direction to early innovation) while also providing an endorsement of specific technologies once they are developed. Whether the subsequent fall in patenting from later standards is problematic is unclear, as, standardization could serve as a coordination mechanism, whereby the quantity of patents falls because standards steer actors away from unpromising research avenues to focus R&D efforts on high reward areas. Thus, the timing of standard setting is important.

The importance of standards is not limited to smart grids. For example, the effectiveness of green and blue hydrogen as a fuel depends on safe storage and distribution. With adaptations to infrastructure, hydrogen could be blended into natural gas to allow transport using existing natural gas pipelines. But equipment modification would be necessary for machines to work with higher concentrations of hydrogen. New pipelines and distribution networks could be built, but standards for safely developing this infrastructure need to be agreed upon. Methods to certify the carbon content of hydrogen are necessary to allow for trade of hydrogen across countries with different climate policies. (IEA, 2019). Standards may play an important role in the development of many enabling technologies.

Building skills for a low-carbon energy transition

Just as enabling technologies prepare energy infrastructure for a low-carbon energy transition, so too must the labor force be prepared to work in a changing energy landscape. Already we see evidence of this challenge, as a shortage of qualified workers has slowed the construction of new nuclear power plants in France (Dalton, 2022). Governments, think-tanks and international organizations have growing interest in developing skills for the low-carbon transition (Cedefop 2019, ILO and Cedefop 2011), especially in the context of the post-Covid recovery packages (IMF 2022). However, understanding how to prepare workers for the low-carbon energy transition is hard due to the lack of appropriate data and widely accepted definitions of green jobs. Many jobs are relatively new—or even currently non-existent—because low-carbon energy technologies are rapidly evolving, so that the required skills are not clear. Recent research applies the task-based approach to labor markets, first developed by David Autor and colleagues (Autor et al. 2003, Autor 2013), to overcome such difficulties in measuring green skills and jobs relevant for a low-carbon energy future (Vona et al. 2018).[6]

Two issues make identifying the jobs that benefit from the large-scale diffusion and development of low-carbon energy technologies difficult. First, it remains conceptually unclear

[6] See Vona (2021) for a detailed discussion of the applications of the task based approach to study the labor market implications of the green transition.

which technologies and productions could be considered ‘green energy’. For instance, there has been a lively debate in the EU on whether gas and nuclear technologies are clean energy technologies eligible for government subsidies. Similar definitional problems apply to occupations specific to these technologies.

Secondly, low-carbon energy jobs are relatively new, and thus not covered in standard occupational classifications. An occupation could be considered ‘green energy’ when it entails the development, production and maintenance of technologies that have the potential to reduce or eliminate GHG emissions, but datasets including detailed information on both occupations and low-carbon energy investments are rare. To illustrate, a car repairer or a construction worker could be green or not depending on the adopted technology and production methods. Unless these classifications are split into sub-groups specific to low-carbon tasks (e.g., electric vehicle car repairer or solar panel installer), one cannot measure the green engagement of an entire occupation.

The task approach to labor markets, when combined with detailed datasets on the task content of occupations, provides a natural framework to improve both the measurement and the conceptual understanding of green occupations. Such an approach has been used to measure occupational exposure to the impact of computers, robots and information and communication technologies (Autor et al., 2003). Its key feature is the distinction between tasks –a unit of work to produce output— and skills—the capability to perform tasks. Factors of production, including workers with different skills, compete to perform each task (Acemoglu and Autor, 2011).

The existing task composition of the economy reflects the current state of the technology. In a subsistence economy, most tasks require physical strength, endurance and informal know-how on plants, animals and weather events. In a knowledge-based economy, problem-solving, verbal and writing abilities become valuable economic inputs. Overall, the process of socioeconomic development involves both the modification of existing tasks and the emergence of new tasks (Vona and Consoli 2015, Acemoglu and Restrepo 2017). Because skills should also be updated to perform new tasks, the task approach allows to examine skill gaps at a very granular level.

For the energy transition, new tasks related to low-carbon energy (e.g., climbing wind towers to inspect and repair or computer and math skills for smart grid management) replace tasks related to coal mining jobs (e.g., operating mining machines to gather coal). The availability of appropriate training or educational programs allows workers to become proficient in skills required to operate low-carbon energy technologies. A greater supply of necessary skills reduces the cost of adopting these technologies. As the development of low-carbon technology unfolds, a skill shortage will represent a key barrier to growth for emerging green industries (DNV 2022). Targeted training programs are known to be more effective than broad training programs (Rodrik and Stantcheva 2021), but reliable information on the specific skills required in specific sectors is often lacking.

Importantly, the willingness of workers to allocate skills to tasks depends on the distribution of wage offers across occupations. A materials engineer may not find it profitable to specialize in wind energy technologies if the wage offered by a wind farm is lower than the wage offered elsewhere in the economy. Wage differences may result from differences in labor productivity. In the case of market imperfections, they may also result from rent sharing. Oil workers may not accept a renewable energy job requiring a similar set of skills if oil jobs offer a higher salary due to rent sharing in the oil sector.

Application of the task approach to the green transition

The task approach has been used only recently to study the labor market aspects of the low-carbon energy transition. Instead, earlier empirical research focused on the spatial dimensions of job gains and losses concentrating on job multiplier effects of industrial activities (Moretti 2010)– i.e., local jobs indirectly created by an energy job. The well-known case is the labor market effects of booms and busts in oil, gas and coal markets. These are extremely concentrated in certain communities (e.g., Black et al. 2005, Marchand 2012) and thus can trigger a political backlash against green policies (Vona 2019, Weber 2020). Recently, this spatial approach has been used to study green job creation in general (Vona et al. 2019) and the specific case of wind and solar energy (Fabra et al. 2022). The task approach complements the spatial approach, and potentially can be combined with it, by informing policymakers on specific retraining requirements for the low-carbon energy transition.

Implementing the task-based approach to study green jobs and skills requires appropriate data. Researchers need data on the task and skill content of occupations. The main dataset with such characteristics is the online Occupational Information Network (O*NET), which is available since 2000. For approximately 1000 occupations, O*NET contains information on both the tasks expected of workers and the skills needed to complete these tasks. Skills potentially apply to all occupations. For each occupation, the skills used are given a one to five importance score. Tasks are unique to each occupation and are text descriptions that can be represented as a binary piece of information. Importantly, O*NET has a special section devoted to identifying green jobs and tasks: the 'Green Economy Program', developed to provide a definition of what is a green job (Dierdorff et al. 2009).

The information contained in the 'Green Economy Program' can be used to identify green jobs based on two types of definitions: i) a binary definition where an occupation is considered either green or non-green; ii) a continuous definition of occupational greenness as the share of the number of green tasks over total tasks.[7] The latter definition, first proposed by Vona et al. (2018 2019), can be interpreted as the amount of time spent on green activities and technologies by the average worker employed in a certain occupation. The continuous indicator provides a more accurate characterization of the exposure of an occupation to green technologies and production. For instance, the binary definition considers construction laborers fully green. Using the continuous definition, their occupational greenness is below 0.3, reflecting the fact that tasks performed by these occupations can be green (i.e. performing building weatherization tasks) or not (i.e., mixing ingredients to create compounds for covering or cleaning surfaces). The share of green employment measured using the continuous indicator is around two to three percent, which is in line with estimates using occasional surveys on green production (e.g. Elliott and Lindley, 2017). The share of green employment using the binary definition is almost 4 times larger.

An accurate measure of occupational greenness allows researchers to identify which skills potentially applicable to all occupations are important for green technologies. Vona et al. (2018) introduce a methodology to identify skills that have a comparative advantage in performing a green task. For over 100 skills included in O*NET, the authors regress a skill's importance score in each occupation on that occupation's greenness indicator, controlling for higher level occupation groups to compare both green and non-green jobs in similar occupations. Using this procedure, they identify sixteen green skills, which are ranked and clustered together using principal component analysis. The resulting four groups of green skills are Engineering and Technical, Operation

[7] See online Appendix B for details.

Management, Monitoring, and Science (see online Appendix B for further details). These green skill indicators help illuminate important aspects of the labor market impacts of green policies. Demand for workers with green skills, especially engineering and technical skills, increases in areas exposed to a more stringent environmental regulation relative to a credible counterfactual.

In the only comprehensive paper covering the low-carbon energy transition, Saussay et al. (2022) use the universe of online job ads in the US to observe directly green (i.e., EV car repairer) and non-green (i.e., traditional car repairer) job posts within an occupation. The job vacancy data allow comparing the skillset of green energy—identified using natural language processing techniques--and non-clean energy ads within very narrow occupational groups. The authors find that a low-carbon energy job ad has a higher skill complexity than similar job ad not only in terms of technical and engineering skills, but also of IT, social and cognitive skills.

To illustrate the importance of green skills, Popp et al. (2021) show that the job creation effect of green spending in the US American Recovery and Reinvestment Act (ARRA) is stronger in local labor markets with a larger pre-existing base of green skills. Overall, green ARRA investments reshaped local economies, leading to permanent job creation for manual and green labor. That the jobs created are primarily manual labor is consistent with the focus of ARRA investments, which included significant funds for energy efficiency retrofits and installation of new wind and solar resources. Compared to the average community, forty percent more jobs were created in communities with the highest prevalence of pre-existing green skills. Thus, workers must have the skills needed in green jobs for green fiscal stimuli to be successful. Relevant to the low-carbon energy transition, the authors show that skill gap between low-carbon energy and fossil fuel workers is modest. However, green jobs require significantly more training. As such, retraining programs reinforcing and developing technical skills are essential to prepare the workforce to the low-carbon energy transition. Connecting the task approach to green skills to earlier work on spatial discrepancies, the authors show that communities whose economies are dependent on fossil fuels have a wide range of green skills. Some such communities, particularly in the West and Midwest have a large share of workers with green skills and appear well-prepared for the low-carbon transition. In contrast, Appalachian communities face both dramatic decreases in demand for coal and a lack of workers with green skills. Thus, skill discrepancies may exacerbate regional inequities associated with the low-carbon energy transition.

Some new evidence on low-carbon energy occupations

The classification of green occupations provided in previous research using O*NET stacks together different environmental problems, without a specific focus on green jobs and skills needed for the low-carbon energy transition. The papers of Saussay et al. (2022) and Popp et al. (2021) are two distinct exceptions. However, the former paper uses confidential data on job vacancy, while the latter focuses on a narrow definition of green energy jobs, mostly focusing on wind and solar occupations

To provide a concrete and novel illustration of the advantages of the task-based approach, we build on Popp et al. (2021) by considering high-skilled occupations only and using a broader, continuous, definition of low-carbon ("green", as in earlier literature) energy occupations (online Appendix B). The broader definition allows us to cover green energy tasks beyond power generation, notably buildings and mobility. The focus on high-skilled occupations is in line with the fact that high-skilled talents are an essential input in the production of new knowledge, which is required to address the remaining challenges of decarbonization. Obviously, low-skilled talents are also essential especially in the production phase of technological development, but the abovementioned work of Popp et al. (2021) is quite exhaustive in this respect.

Finally, we enrich previous analyses on the skill content of green jobs by pairing information on skill requirements from O*NET with data on the main field of study of workers from recent waves of the American Community Survey (see online Appendix C for details). Education data capture part of the adjustment in the supply side of workers.

Table 2: Skill profiles of Green Energy, Brown Energy and Other Similar Occupations

	Green energy HS occ	Brown fossil HS occ	Other: 3-digit HS occ with at least 1 green energy
Share of tot employment	1.05%	0.02%	11.31%
Hourly wage	38.45	46.16	34.23
Education and training			
Required years of educ (from O*NET)	15.68	16.88	15.33
Required years of training (from O*NET)	2.37	1.85	2.03
Years of education (from ACS)	14.78	16.10	14.69
College share (from ACS)	59.48%	90.87%	56.44%
Post-graduate share (from ACS)	20.92%	39.13%	21.35%
*Skills measure from O*NET (range 1-5)*			
Green Skill: eng & tech	2.93	2.85	2.37
Green Skill: operation manag	3.47	3.60	3.44
Green Skill: science	2.20	3.05	1.80
Green Skill: monitoring	3.54	3.32	3.42
Field of study			
Degree in STEM fields	27.97%	59.44%	14.89%
Degree in Engineering fields	22.48%	21.31%	9.96%
Degree in STEM fields (if graduate=1)	47.02%	65.41%	26.38%
Degree in Engineering fields (if graduate=1)	37.79%	23.45%	17.65%

Notes: elaboration from American Community Survey, average 2009-2019, data and O*NET data 24.0.

Table 2 presents the profiling of high-skilled (HS) green energy, brown energy and other occupations (neither green nor brown) in a 3-digit SOC group that contains a green energy occupation, so that we compare the characteristics of similar occupations. Green energy employment is weighted by the product of each occupation's employment share and greenness as in Vona et al. (2019). These weights take advantage of the task-based definition of green employment, where many occupations are only partially green. Note first that green energy HS occupations represent slightly more than one percent of total employment, while high-skilled brown energy occupations only 0.02 percent. This exceeds estimates using job vacancy data (Saussay et al., 2022) because—to observe the field of study—we use American Community Survey data that are slightly more aggregated than Bureau of Labor Statistics data, leading to a well-known overstatement of the size of the green economy (see Vona 2021 for details).

On average, green energy HS workers earn 12.3 percent more than other HS occupations, but twenty percent less than HS brown energy ones. This is consistent with the well-known rent sharing in fossil fuel sectors, but it is also explained by a higher intensity of all the human capital measures presented in the table. Next, the green wage gap between green and other occupations is not matched by similar gaps in the educational level required (from O*NET) or observed (from ACS). As in Popp et al. (2021), green energy jobs require more on-the-job training, but four additional months of training can hardly account for a green wage gap of 12.3 percent. The second panel of the Table highlights differences in O*NET-based measures of skills that reflect the competences demanded by employers. Not surprisingly, we observe a very large gap in two out of four green skills, namely engineering and science skills. Because the use of science and engineering skills in the workplace is positively correlated with earnings, this gap could partly explain the green wage gap.

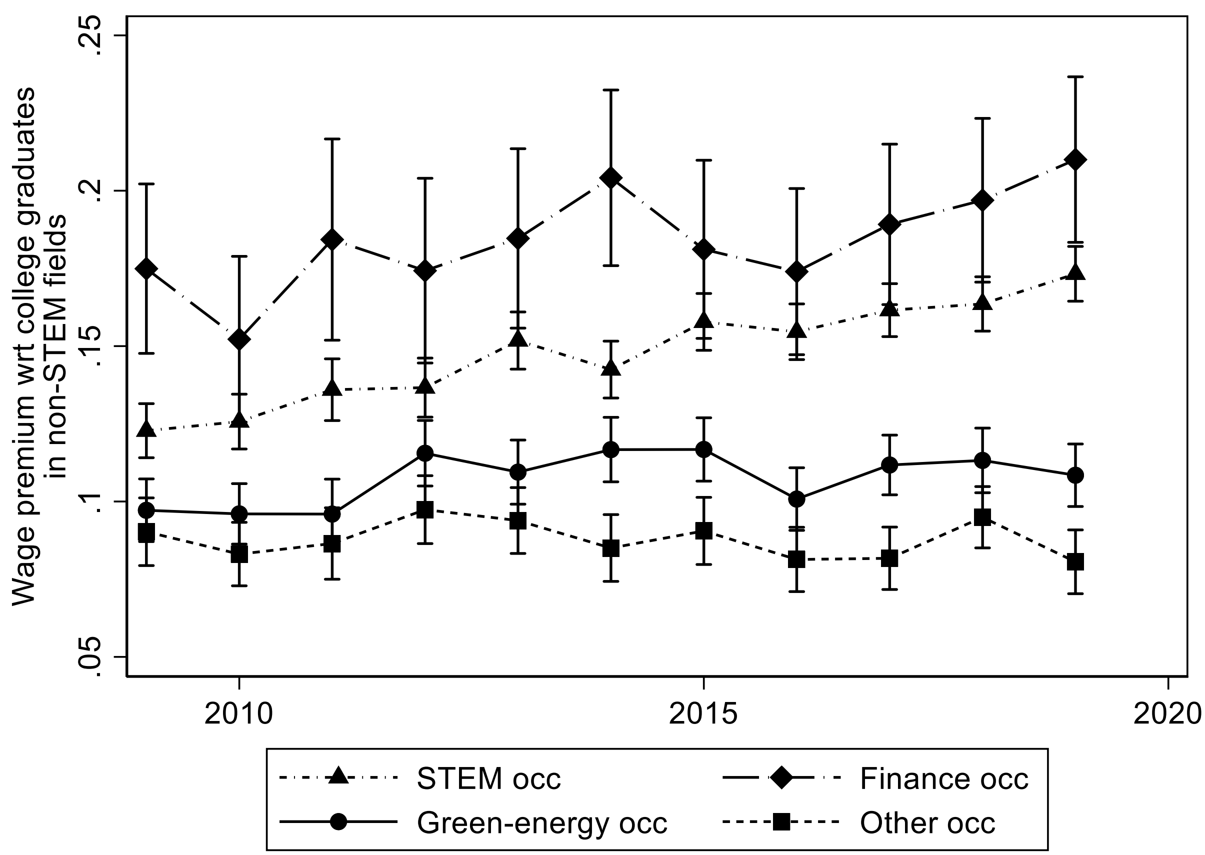
The last panel of the Table uses data on field of study to illustrate the Science, Technology, Engineering and Mathematical (STEM)-bias of green occupations. Green energy occupations are more STEM-intensive than similar occupations. STEM graduates, particularly in engineering, are more likely to work in the low-carbon energy sectors. Relative to similar occupations, a STEM graduate is almost twice as likely to work in green energy occupations than in similar occupations. This implies that STEM talents seem to have the right incentives to work in green energy jobs, thus enhancing the US green innovation potential.

However, competition for STEM talents has increased tremendously in recent decades. This has not been caused by the fracking boom as brown energy jobs absorb just a very tiny fraction of STEM talents. Rather, competition of fintech and digital giants attracts more STEM talents (Marin and Vona 2022). To shed light on the incentives of STEM graduates to work in green energy occupations with respect to finance and other high-tech occupations, we estimate the returns of STEM graduates in different occupations, conditional on a host of intervening factors that are standard in wage regressions (see online Appendix C for details). A virtue of the task approach rests indeed in the possibility to evaluate the returns of different skill-task matches at the worker level. Figure 3 plots the worker-level estimates of the returns to STEM graduates in four different positions (finance occupations, STEM non-green occupations, green energy occupations and other non-STEM occupations[8]) relative to the baseline category of any other college graduate. We find that STEM graduates earn significantly more in finance or in STEM occupations than in green energy occupations, and that the gap is widening over the last four years. Still, the descriptive evidence presented in Table 2 shows that STEM graduates go to work in clean energy jobs. However, Figure 3 suggests that the brightest STEM talents will be more attracted by other innovative sectors, such as fintech, algorithmic trading and AI, limiting the global innovative capabilities in green energy technologies. This is just a conjecture that should be corroborated by

[8] We do not include fossil-fuel jobs in the comparison because they are too few STEM graduates working in such occupations in the ACS dataset.

richer and more detailed analyses. The goal here is to propose an approach that enables studying issues related to skill gaps, reallocation costs and potential talents' misallocation towards "less socially desirable" technological trajectories.

Figure 3: Estimated returns of STEM degrees in different occupations



Notes: elaboration on ACS data. Point estimates and confidence intervals 95% level are reported. Returns to STEM graduates are weighted by sampling weights. Only college graduates in high-skilled occupations aged between 22 and 64 are included in the estimation sample. Regressions are weighted using person sampling weights. Standard errors clustered by industry, occupation and age group in parenthesis. Further details on the regressions are given in online Appendix C.

Conclusions

The energy transition is entering a new phase, where further cost reductions are not enough. If net zero carbon emission goals are to be met, developing complementary physical and human capital that reduce the cost of low-carbon energy adoption and enable low-carbon energy to be applied more broadly will be necessary. Technologies that store energy or improve grid management make it easier to integrate intermittent renewable sources into electricity grids. Increased penetration of electric vehicles requires mechanics trained to work on them.

To promote innovation on enabling physical capital technologies, we note the important role of targeted demand and supply side policies emphasized in recent literature on energy innovation. Broad-based technology neutral policies incentive the use of least cost technologies. But simply relying on technologies already market-ready cannot deliver a zero carbon economy. Developing complementary technologies or technologies for niche markets requires a portfolio of policies that target specific technological needs. To provide inventors as much room as possible to devise innovative solutions, governments choosing to implement such policies should identify and target market failures serving as barriers to needed technologies.

The complementarity between technologies, as well as between capital and labor, also require attention. Smart-grids provide an example where technology standards play a guiding role so that a diverse set of technologies can work together. Yet this is just one example. Standards will play important roles for developing electric vehicle charging infrastructure or the provision and delivery of hydrogen energy.

But innovation does not stop with physical capital. Changing technology requires a changing workforce. Using the task-based approach to labor, we discussed the skills likely to be in demand in a clean-energy economy. Informing policymakers on the exact type of skills and education required is possible only with a granular approach such as that proposed within the task model. Low-carbon energy jobs make more intensive use of STEM skills such as science and engineering than other comparable jobs. Note that some engineering and technical skills (e.g., mechanics, building and construction) are not necessarily correlated with higher level of formal education, which is consistent with the fact that green occupations require more on-the-job training than similar occupations. Governments have a natural advantage to invest in training and new educational programs for green jobs, given the high fixed costs characterizing such investments

While the impact on workers shares many similarities to the impact of innovation on physical capital, there are also important differences. Low-carbon energy policy aims to make inefficient, dirtier technologies obsolete. That is part of the point. But doing so risks making some workers skills obsolete as well. Green jobs require workers with STEM skills, but also pay less than many other STEM-intensive occupations. Simply within the energy sector, fossil fuel workers earn higher wages. Workers don't want to be retrained to move to a sector that pays theme less. Addressing the distributional issues of energy policy on workers is important to gain political support for low-carbon energy policies.

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Appendix A: CPC classifications for energy technologies

<u>Clean Energy Technologies</u>

Building Energy Efficiency

Y02B 20/00	Energy efficient lighting technologies, e.g. halogen lamps or gas discharge lamps (and all of its subclasses: 20/30, 20/40, 20/72)
Y02B 30/00	Energy efficient heating, ventilation, or air conditioning [HVAC] (and all of its subclasses: 30/12, 30/13, 30/17, 30/18, 30/52, 30/54, 30/56, 30/62, 30/625, 30/70, 30/90)
Y02B 40/00	Technologies aiming at improving the efficiency of home appliances, e.g. induction cooking or efficient technologies for refrigerators, freezers or dish washers (and all of its subclasses: 40/18)
Y02B 50/00	Energy efficiency technologies in elevators, escalators, and moving walkways, e.g. energy saving or recuperation technologies
Y02B 80/00	Architectural or constructional elements improving the thermal performance of buildings (and all of its subclasses: 80/10, 80/22, 80/32)

Solar photovoltaic (PV)

Y02E 10/50	Photovoltaic (PV) energy (and all of its subclasses: 10/52, 10/541, 10/542, 10/543, 10/544, 10/545, 10/546, 10/547, 10/548, 10/549, 10/56)

Wind energy

Y02E 10/70	Wind energy (and all of its subclasses: 10/72, 10/727, 10/728, 10/74, 10/76)

Hybrid and Electric Vehicles

Y02T 10/62	Hybrid vehicles
Y02T 10/64	Electric vehicles
Y02T 90/14	Plug-in electric vehicles

Enabling Technologies

Smart grids (except for vehicle charging)

Y02B 70/30	Systems integrating technologies related to power network operation and communication or information technologies for improving the carbon footprint of the management of residential or tertiary loads, i.e. smart grids as climate change mitigation technology in the buildings sector, including also the last stages of power distribution and the control, monitoring or operating management systems at local level (and all of its subclasses: 70/3225, 70/34)
Y02B 90/20	Smart grids as enabling technology in the buildings sector
Y02E 40/70	Smart grids as climate change mitigation technology in the energy generation sector
Y04S 10/00	Systems supporting electrical power generation, transmission or distribution (and all its subclasses: 10/12, 10/123, 10/126, 10/14, 10/16, 10/18, 10/20, 10/22, 10/30, 10/40, 10/50, 10/52)
Y04S 20/00	Management or operation of end-user stationary applications or the last stages power distribution; Controlling, monitoring or operating thereof (and all of its subclasses: 20/12, 20/14, 20/20, 20/221, 20/222, 20/242, 20/244, 20/246, 20/248, 20/30).
Y04S 40/00	Systems for electrical power generation, transmission, distribution or end-user application management characterised by the use of communication or information technologies, or communication or information technology specific aspects supporting them (and all of its subclasses: 40/12, 40/121, 40/124, 40/126, 40/128, 20/18, 40/20).
Y04S 50/00	Market activities related to the operation of systems integrating technologies related to power network operation and communication or information technologies (and all of its subclasses: 50/10, 50/12, 50/14, 60/16).

Electric vehicle charging

Y02T 90/12	Electric charging stations
Y02T 90/167	Systems integrating technologies related to power network operation and ICT for supporting the interoperability of electric or hybrid vehicles, i.e. smart grids as interface for battery charging of electric vehicles [EV] or hybrid vehicles [HEV] (NOTE: documents tagged under Y02T 90/167 are concurrently tagged under Y04S 30/10)
Y04S 30/00	Systems supporting specific end-user applications in the sector of transportation (and all of its subclasses: 30/10, 30/ 12, 30/14)

Energy storage using batteries

Y02E 60/10	Energy storage using batteries

Hydrogen and fuel cells

Y02E 60/30	Hydrogen technology (and all of its subclasses: 60/32, 60/36)
Y02E 60/50	Fuel cells

Appendix B: Green Skills Data Sources and Measures

Occupational Information Network. O*NET is the standard data source to implement the task-based approach since 2000. The predecessor of O*NET is the US Dictionary of Occupation and Titles (DOT), developed in 1939 by the United States Employment Service. Experts rated the extent to which a particular task (e.g. handling and moving objects) or skill (e.g. math) is important in an occupation. Rates were assigned either on a 1-to-5 scale or as a dichotomous variable (yes/no). After reaching its revised 4th edition in 1991, the DOT was replaced by the online Occupational Information Network (O*NET) in 2000.[9] Not only has O*NET dramatically expanded the range of skills and work activities (from around 44 in DOT to more than 400 in O*NET), but it has also added detailed text descriptions for a sub-set of tasks specific to each occupation.[10] More specifically, O*NET contains information on both tasks (e.g. what workers are expected to do at the workplace – the 'demand side') and skills (e.g. the abilities and competences that workers should possess to perform work tasks - the 'supply side'). Skills are defined for all occupations with a 1-5 importance score attached, while tasks are text descriptions unique to each occupation and thus can be represented as a binary piece of information. The downside of O*NET is that occupational descriptions are available for only 900 occupations.[11] In turn, DOT defines skill contents at the level of approximately 12,000 job titles, where a job title can be seen as the most granular sub-level of an occupation. The O*NET data have been used in countless applications in labor economics, published in both top general and field journals in the discipline.

O*NET has a special section devoted to identifying green jobs and tasks: the 'Green Economy Program' (maintained together with the US Department of Labor), developed to provide a definition of what is green and is mostly inspired by the *output definition* (see Dierdorff et al., 2009). The information contained in the 'Green Economy Program' can be used to identify green jobs based on two types of definitions: i) a binary definition where an occupation is considered either green or non-green; ii) a continuous definition of occupational greenness that, as we will see, exploits information on the greenness of the task content of occupations.

[9] The interested reader can explore the online resources of O*NET: https://www.onetonline.org/ and the entire database: https://www.onetcenter.org/database.html#individual-files.
[10] O*NET also changed the methodology to collect the data from using only expert judgement to the combination of expert judgment and incumbents' surveys.
[11] This roughly corresponds to the 6/8-digit level of Standard Occupational Classification (SOC).

Occupational greenness indicator is defined as the ratio between the number of green specific tasks and the total number of specific tasks done in occupation k:

$$Greenness_k = \frac{\#green\ specific\ tasks_k}{\#total\ specific\ tasks_k}.$$

The Greenness index varies continuously between zero and one.

Table B1: Green Skills (from Vona et al., 2018)

	Engineering & Technical
2C3b	Engineering and Technology
2C3c	Design
2C3d	Building and Construction
2C3e	Mechanical
4A3b2	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment
4A1b3	Estimating the Quantifiable Characteristics of Products, Events, or Information
	Operation Management
2B4g	Systems Analysis
2B4h	Systems Evaluation
4A2b3	Updating and Using Relevant Knowledge
4A4b6	Provide Consultation and Advice to Others
	Monitoring
2C8b	Law and Government
4A2a3	Evaluating Information to Determine Compliance with Standards
	Science
2C4b	Physics
2C4d	Biology

Green skills, further details. The detailed list of the 16 green skills is provided in Table B1. *Engineering and Technical skills* encompass skills required in several stages of technology, including design, construction and installation. As shown in Vona et al. (2018), these skills are very important also in low- and middle-skills occupations such as Solar Installers, Weatherization Workers and Technicians. *Operation Management skills* are associated with new organizational practices needed in greener activities; in particular, with continuous assessment and adaptive business practices. Relevant examples of professions intensive in Operation Management skills are Sustainability Specialists, Chief Sustainability Officers and Supply Chain Managers. *Monitoring skills* include legal, administrative and technical activities necessary to comply with regulatory standards. Key occupations using these skills intensively include Environmental

Compliance Inspectors and Emergency and Management Directors and Legal Assistants. *Science skills* are obviously important in the first stages of the innovative process. Occupations with high scores in this skill can either have specific knowledge applicable to environmental issues, such as Materials Scientists or Hydrologists, or be more general know-how, such as Biophysicists and Biologists.

Green and brown energy occupations. The lists of green energy and brown energy occupations are reported in Tables B2 and B3, respectively. The list of green energy occupations also reports the greenness index. The lists are broader than those considered by Popp et al. (2021). While our analysis focus in the paper is on high-skilled green energy occupations only, for sake of completeness we report the low-skilled ones as well. High-skill occupations comprise SOC groups between 11 and 29. Green energy STEM occupations are those contained in the three broad STEM occupational groups: SOC 13, SOC 17 and SOC 19. To provide an example of a green energy occupation, consider the occupation “Electrical Engineer”. The occupation has a greenness of 16%, meaning that the average electrical engineer in the US works 16% of the time on green tasks. Examples of non-green tasks for this occupation are “Design, implement, maintain, or improve electrical instruments, equipment, facilities, etc.” or “Prepare specifications for purchases of materials or equipment”. Example of green energy tasks are “Develop systems that produce electricity with renewable energy sources, such as wind, solar, or biofuels” or “Integrate electrical systems with renewable energy systems to improve overall efficiency”.

Table B2: List of green energy occupations used in the paper

soc2018	description	greenness
11-3071.00	Transportation, Storage, and Distribution Managers	0.185
11-9021.00	Construction Managers	0.251
11-9041.00	Architectural and Engineering Managers	0.178
11-9041.01	Biofuels/Biodiesel Technology and Product Development Managers	1.000
11-9199.01	Regulatory Affairs Managers	0.111
11-9199.02	Compliance Managers	0.174
11-9199.09	Wind Energy Operations Managers	1.000
11-9199.10	Wind Energy Development Managers	1.000
13-1041.07	Regulatory Affairs Specialists	0.144
17-2011.00	Aerospace Engineers	0.461
17-2051.00	Civil Engineers	0.452
17-2051.01	Transportation Engineers	0.179
17-2071.00	Electrical Engineers	0.161
17-2072.00	Electronics Engineers, Except Computer	0.197
17-2081.00	Environmental Engineers	1.000
17-2141.00	Mechanical Engineers	0.277
17-2141.01	Fuel Cell Engineers	1.000
17-2141.02	Automotive Engineers	0.298
17-2161.00	Nuclear Engineers	0.331
17-2199.03	Energy Engineers, Except Wind and Solar	0.953
17-2199.10	Wind Energy Engineers	1.000
17-2199.11	Solar Energy Systems Engineers	1.000
17-3023.00	Electrical and Electronic Engineering Technologists and Technicians	0.212
17-3027.01	Automotive Engineering Technicians	0.278
17-3029.08	Photonics Technicians	0.146
19-2021.00	Atmospheric and Space Scientists	0.462
19-2041.01	Climate Change Policy Analysts	1.000
19-2099.01	Remote Sensing Scientists and Technologists	0.072
19-3051.00	Urban and Regional Planners	0.360
19-4042.00	Environmental Science and Protection Technicians, Including Health	1.000
19-4043.00	Geological Technicians, Except Hydrologic Technicians	0.144
19-4051.00	Nuclear Technicians	0.384
19-4099.03	Remote Sensing Technicians	0.116
41-4011.07	Solar Sales Representatives and Assessors	1.000
47-2061.00	Construction Laborers	0.158
47-2152.04	Solar Thermal Installers and Technicians	1.000
47-2181.00	Roofers	0.301
47-2211.00	Sheet Metal Workers	0.214
47-2231.00	Solar Photovoltaic Installers	1.000
47-4011.00	Construction and Building Inspectors	0.264
47-4011.01	Energy Auditors	1.000
47-4099.03	Weatherization Installers and Technicians	1.000

49-3023.00	Automotive Service Technicians and Mechanics	0.440
49-9021.00	Heating, Air Conditioning, and Refrigeration Mechanics and Installers	0.132
49-9071.00	Maintenance and Repair Workers, General	0.135
49-9081.00	Wind Turbine Service Technicians	1.000
49-9099.01	Geothermal Technicians	1.000
51-8011.00	Nuclear Power Reactor Operators	0.275
51-8013.00	Power Plant Operators	0.601
51-8013.03	Biomass Plant Technicians	1.000
51-8013.04	Hydroelectric Plant Technicians	1.000
51-8099.01	Biofuels Processing Technicians	1.000
53-6051.07	Transportation Vehicle, Equip. and Systems Inspect., Except Aviation	0.436

Notes: authors' elaborations from O*NET 24.0 dataset

Table B3: List of brown energy occupations used in the paper

soc2018	Description
17-2151	Mining and Geological Engineers, Including Mining Safety Engineers
17-2171	Petroleum Engineers
19-2042	Geoscientists, Except Hydrologists and Geographers
47-5011	Derrick Operators, Oil and Gas
47-5012	Rotary Drill Operators, Oil and Gas
47-5013	Service Unit Operators, Oil and Gas
47-5041	Continuous Mining Machine Operators
47-5061	Roof Bolters, Mining
53-7033	Loading and Moving Machine Operators, Underground Mining
47-5071	Roustabouts, Oil and Gas
47-5081	Helpers--Extraction Workers
51-8013	Power Plant Operators
51-8092	Gas Plant Operators
51-8093	Petroleum Pump System Oper., Refinery Oper., and Gaugers
53-7072	Pump Operators, Except Wellhead Pumpers
53-7073	Wellhead Pumpers
47-5043	Roof Bolters, Mining
47-5044	Loading and Moving Machine Operators, Underground Mining

Notes: source SOC 2018 classification

Appendix C: STEM Wage Data Sources and Methods

American Community Survey Data. The main source of information about STEM degrees and to estimate the green wage premium for STEM workers is the American Community Survey (ACS). From 2000, this survey retrieves demographics (e.g., gender, age, ethnicity) and socioeconomic information (e.g., educational attainment, occupation, wage, sector of work) for a 1% representative sample of the US population. The individual-level data are publicly available in the Integrated Public Use Microdata Series, known as IPUMS. For the purposes of this paper, we only use ACS data for the period 2009-2019 where information on the degree field of study is available. We focus our attention on employed individuals in working age (16-64 years old, or 22-64 when we consider the sub-sample of college graduates).

The partition of the degree field of study into Science, Technology, Engineering and Math and non-STEM is standard in the literature (see Marin and Vona 2022). Following Marin and Vona (2022) and the associated literature in labor economics, we classify as STEM the occupation belonging to SOC groups 15 (computer and math occupations), 17 (architecture and engineering) and 19 (life and physical scientists, but excluding social scientists). A STEM graduate working is a STEM occupation is a "natural matching". A STEM graduate is a graduate in the following field of study: science; computer science; math and engineering. Because some STEM occupations are green, we further partition the group of STEM occupations into green and non-green. Non-green STEM occupations are all the 6-digit occupations in SOC groups 15, 17 and 19 that are not included in Table B2.[12] Finally, Marin and Vona (2022) find that the returns to STEM reach the highest level in finance occupations, thus we consider the group of finance occupations (SOC 13-2, financial specialists, and SOC 11-3031, financial manager).

More details on the estimating equation.

Here, we provide essential details on the methodology used to estimate the returns to STEM graduates in different occupations. For further details, the interested reader can refer to the related paper of Marin and Vona (2022).

We compare the wage of a STEM graduate in occupations where STEM skills are more important (finance, non-green STEM occupations and green STEM occupations) with the wage of

[12] A complete list of 6-digit SOC occupations can be found here: https://www.bls.gov/oes/current/oes_stru.htm.

a STEM graduate in any other occupations, i.e., the benchmark category. For each year between 2009 and 2019, we estimate the following equation at the individual i level:

$$\log(w_i) = \varepsilon_i + \mathbf{X}_i'\boldsymbol{\theta} + \beta_1 STEM_i + \beta_2 finance\_occ_k + \beta_3 finance\_occ_k \times STEM_i \\ + \beta_4 STEM\_occ_k + \beta_5 STEM\_occ_k \times STEM_i + \beta_6 greenness_k + \beta_7 greenness_k \\ \times STEM_i,$$

where the dependent variable is the log of the hourly wage, ε_i is an error term and $\mathbf{X}_i'$ a vector of standard controls in wage equations.[13] The variable of interests are: i. $STEM_i$, dummy equal one for worker with a STEM degree; ii. $finance\_occ_k$, a dummy equal one for workers in finance occupations; iii. $STEM\_occ_k$, a dummy equal one for workers in finance occupations; iv. $greenness_k$, the occupational greenness defined above; the full set of interaction between STEM degree, on the one hand, and occupational dummies/greenness, on the other. Thus, the returns to STEM are estimated exploiting variation across occupations conditional on a very rich set of controls, which however does not fully eliminate concern for non-random sorting of workers with different unobservable skills in different occupations.

For each year, the plotted returns to STEM in green occupations are obtained as follows: $\hat{\beta}_1 + \hat{\beta}_6\overline{greenness}+\hat{\beta}_7\overline{greenness}$. Plotted returns in finance (resp. STEM) occupations are: $\hat{\beta}_1 + \hat{\beta}_2+\hat{\beta}_3$ (resp. $\hat{\beta}_1 + \hat{\beta}_4+\hat{\beta}_5$).

[13] These controls are: 2-years bins of age interacted with gender, 2-digit NAICS sector dummies, metro-area dummy, dummy for married individuals, dummy for black individuals, dummy for other non-white individuals, dummy for foreign-born individuals, a dummy for individuals with post-graduate education, occupation-level importance of math skills and social skills from O*NET. Regressions are weighted using person sampling weights. Only college graduates aged between 22 and 64 are included in the estimation sample. Standard errors clustered by industry, occupation and age group in parenthesis.