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Finance in global transition scenarios: Mapping investments by technology into finance needs by source

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ABSTRACT

Numerous studies have presented scenarios regarding energy transition, including the computation of investment costs in various models. Although these studies project detailed investment pathways for different technologies, they do not distinguish between different sources of and types of funding. They tell us what the transition will cost, but not how it will have to be financed. In this paper, we develop a methodology according to which an appropriate financing mix can be calculated from these investment projections based on technology-related assumptions in scenarios. We differentiate between debt and equity as well as between the following sources: public/private Research, Development and Demonstration (RD&D), small-distributed financing, venture capital (equity), public markets (equity), and asset finance (debt and equity provided by institutional investors). We show that major commitments to wind and solar energy need to come from institutional investors in the form of asset finance. In addition, to achieve the transition to a decarbonized power system, government and private investors need to continue investing and extend their engagement in funding research, demonstration, and early deployment. Finally, we present a number of policy options targeting the different sources of finance.

1. Introduction

To reach the targets set by the 2015 Paris Agreement, a significant reduction in CO_2 emissions is necessary (IPCC, 2019; OECD/IEA and IRENA, 2017; Rockström et al., 2017), and many studies have projected the required amount of investment in renewable energy (RE) production and/or reduced energy demands to make this happen (see Fig. 1). These investments are, without exception, large and cover both investment in the deployment of mature technologies and the development of new and innovative technologies (Eyraud et al., 2013; Mathews et al., 2010; Polzin, 2017). It is well known from the finance literature, however, that different investments attract very different types of investors, with correspondingly different mandates, risk appetites, and loss-absorbing capacities (Mazzucato and Semieniuk, 2018; Polzin et al., 2017). It is therefore important to consider not only the total amount, but also the mix in which finance should be available to make the energy transition feasible.

Fig. 1 shows the projected average annual investments per technology for a selection of models. These projections show that there is significant variation across models and scenarios; however, what the underlying studies do not explicitly address is what sources of finance actually need to be tapped to finance the total investments in these different technologies. Preliminary work (Mazzucato and Semieniuk, 2018; Polzin and Sanders, 2020) indicates that a qualitative mismatch rather than an actual financing gap may slow down the energy transition. This is, in a sense, good news, as it is easier to redirect available resources than to overcome absolute shortages. Specifically, we need to design policies to better engage private sector financiers. To design such policies, however, we first need to assess and quantify their role in the scenarios covering 2020–2050 (McCollum et al., 2018). McCollum et al. (2013, p. 3) already asserted that "what this mix of investments [sources of finance] should look like is very much an open question, however, especially at the national and regional level." To address this gap in the literature, we propose a simple method for mapping the readily available and routinely projected vector of investments per technology into a vector of investments according to preferred financing types.

The intuition behind the approach in this paper is straightforward: We extrapolate the financing needs by technology over the next several decades from existing scenarios. First, we assume that investment in these technologies will require a similar financing mix over this period. This admittedly strong assumption is based on a preliminary analysis of the financing dynamics over the 2006–2016 period that showed no clear trends in the financing mixes of the technologies we study. One might argue, however, that the mix is likely to shift over longer timespans, as technologies mature and experience makes risks more

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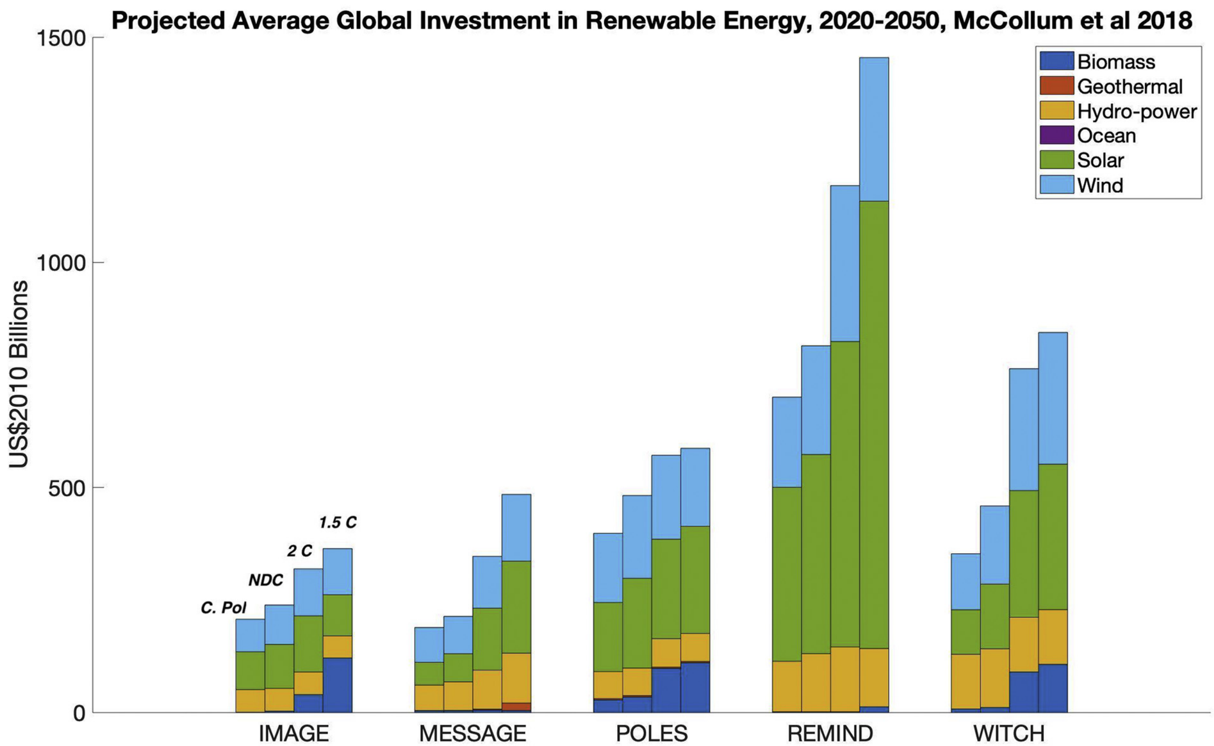

Fig. 1. Financing needs across different models and scenarios; average annual investments (2016–2050) in USDbn (2015) (Source: McCollum et al., 2018). C. Pol = Current Policies; NDC = National Determined Contributions; 2C = 2C compatible scenario; 1.5C = 1.5C compatible scenario.

manageable (e.g., Egli et al., 2019). On one hand, such extensions can easily be accommodated in our framework when empirically validated dynamics become more readily available. On the other, we should realize that investment in a technology always implies investment in a portfolio of projects, ranging from developing the next to scaling the current and scrapping the previous generations of a technology. Second, we aggregate the financing need by finance source to arrive at a required financing mix for 2020–2050. This mix can be differentiated by technology and by type of finance. Our method allows modelers and scenario builders to not only produce projections for the total amount of investment per technology but also split these numbers into public and private types of investments. This allows policy makers to signal qualitative mismatches in the supply and demand for funds and thus better target their public resources to overcome barriers in the energy transition.

The remainder of this paper is organized as follows: Section 2 presents the conceptual background and positions our work in the literature. Section 3 describes the proposed methodology, and Section 4 presents our data and results. Section 5 briefly digresses into the important issue of (financial) learning curves and technology life cycles. We believe this to be an important avenue for future research in this area. Lastly, Section 6 takes stock and concludes.

2. Conceptual background

Mercure et al. (2019) discuss the representation of the financial sector in macroeconomic models and assert that the energy-modeling literature has largely neglected the role of finance and money (e.g., Grubb, 2002). If finance is addressed explicitly, most models use common and simplifying assumptions to describe financial markets. According to the efficient market hypothesis (EMH) and the Modigliani-Miller Theorem (Modigliani and Miller, 1958), for example, capital is abundant and available in the required form at the appropriate price, as long as financial market actors possess enough information on the projects under consideration. In this view, which is dominant in most computable general equilibrium (CGE) and integrated assessment models (IAMs), money is seen as a commodity, and investment is only constrained in the aggregate by the total savings in the economy. These studies compute the investment needs of technologies across different scenarios (e.g., business-as-usual, nationally determined contributions and transformational pathways compatible with 2 °C or 1.5 °C global warming) (e.g., Bauer et al., 2017; Capros et al., 2018; IPCC, 2019; McCollum et al., 2018) and typically produce a required total amount often split over a set of investigated technologies in USDmn/bn annually over a number of years or decades.

According to these projections, current investment levels in low-carbon technologies fall short by around 70% of the investment needs to achieve a 2 °C compatible emission level by 2050. This has been attributed to commercialization risk (relative immaturity) and dependence on public and financial institutions designed for different investment profiles (Granoff et al., 2016). Other studies have highlighted the high capital intensity, low operational costs, and misfits in market design as additional barriers (Bolton et al., 2015; Newbery et al., 2018; Tietjen et al., 2016). Banks and institutional investors such as pension funds and insurance companies especially shy away from engaging more in the energy transition (Campiglio, 2016). Recent attempts to bring institutional investors into the RE sector (recommendations on climate-related financial disclosures, the European Union [EU] green taxonomy, etc.) are valuable yet incomplete. Moreover, these studies have ignored the fact that the technologies in transition scenarios are located in different stages of the "financing life cycle," and investment in all stages is required for the projected diffusion to take place at the necessary speed.

In accordance with the EMH, simulation models (often implicitly) assume that investments in research and development (R&D), innovation, and deployment can all be financed at similar (risk-adjusted) interest rates. That is, a single discount rate and weighted average cost of capital is typically assumed, either for all technologies differentiated by country (e.g., Iyer et al., 2015) or across all technologies and countries (e.g., Bogdanov et al., 2019). In other words, the problem of matching the mix of required and available financial resources by source is assumed away. Given the barriers to the early stages of the innovation process and in the later diffusion stages, these are strong assumptions (Owen et al., 2018). Recent contributions to the literature have questioned the efficiency of financial markets, especially since the financial crisis of 2008 and in the context of an ongoing transition (Ameli et al., 2019; Hall et al., 2015). Yet, even under the EMH, the different risk-return profiles of technologies over their life cycles would imply that financing costs will change over time as technologies mature and fundamental uncertainty is reduced to calculable and diversifiable risk.

These dynamics are related to the adaptive market hypothesis (Hall et al., 2015; Soufian et al., 2014) in which the behavior of investors plays an important role. When investors are slow to adapt their expectations and need to improve their expertise on new technologies and projects, finance may be expensive and in limited supply. Recent work (Egli et al., 2018; Schmidt et al., 2019) has highlighted learning in the financial sector and the importance of interest rates for the energy transition, as capital expenditure drives the costs for most RE technologies. Even if the main climate externality were addressed by a global CO_2 price or a cap-and-trade system, financing gaps could persist due to other market failures related to the characteristics of the different types of finance (Kim and Park, 2016; Polzin, 2017).

The financial needs for a transition towards a low-carbon and RE system involve a variety of investors and financial intermediaries. To effectively mobilize the required mix of public and private sources of finance, it is therefore important to map the investment needs of technology into a mix of suitable financing sources. In a second step, these can be compared to the available mix in current financial market structures, and mismatches that may be related to restrictive mandates and regulatory or market barriers that different actors face can be identified. In this paper, we propose a methodology for doing this, which both contributes to the discussion around financing the transition to a clean energy system (Anbumozhi et al., 2018; Blyth et al., 2015; Eyraud et al., 2013; Mazzucato and Semieniuk, 2018) and complements existing model-based work on energy transition scenarios (e.g., Barton et al., 2018; IPCC, 2019; McCollum et al., 2018, 2013).

3. Methodology for estimating financing needs by source

The typical energy transition scenario simulation in a model generates a projected deployment path for a variety of technologies over time (van Sluisveld et al., 2015). Using load factors, projected production levels can be turned into required installed capacity, which may then be multiplied by a projected cost per installed capacity to obtain a total required investment per technology per year. To turn that into a projected total required investment per financing source, we needed a matrix that would allow us to multiply a vector of total investments per technology (per year) into a vector of total investments per financing source (per year). Assume that we wanted to distinguish $m \in M$ sources of finance in a model that distinguishes $n \in N$ technologies for $t \in T$ years, we would use

$$\begin{bmatrix} x_1^1 & . & x_1^N \\ . & . & . \\ x_M^1 & . & x_M^N \end{bmatrix} \times \begin{bmatrix} I_t^1 \\ . \\ I_t^N \end{bmatrix} = \begin{bmatrix} I_t^1 \\ . \\ I_t^M \end{bmatrix} \tag{1}$$

in order to compute the financing demand by source for year t. We thus need to create or estimate an $M \times N$ matrix of coefficients, x_m^n, to represent the share of financing source m in total investment in technology n. By assuming that these coefficients are time-invariant, we can use the time variation in data from the (recent) past to compute them. This time invariance is supported by our preliminary analysis of the data in Section 5 and the fact that the coefficients will be applied to investment projections for technologies that include a level of technological learning, particularly in REMIND-MAgPIE (McCollum et al., 2018, SI). For example, new forms of wind turbines will be researched, developed, and deployed at roughly the same relative intensity in the future as they were in the recent past. We thus assumed that the portfolio of projects and assets in each technology was in a steady state in the recent past, and we provide a sensitivity analysis in Section 4. In Section 5 below, we briefly discuss possible extensions to our framework to include financial learning and allow for changing life cycle dynamics across sectors and technologies.

Ideally, one would compute the coefficients x_m^n in the $M \times N$ matrix in Eq. (1) from a dataset that distinguishes investments in energy technologies by source and technology over time. Unfortunately, to the best of our knowledge, such data is not publicly available. Therefore, to estimate the coefficients, we resorted to the next best thing. We took the data on investments across M sources (I_t^m) and data on investments across N technologies (I_t^n) during the 2006–2016 period from the Bloomberg New Energy Finance (BNEF) database[1]. This period suited our scope of analysis, as it corresponds to the major increase in RE investments globally and bookends the financial crisis. We then computed the average shares of these sources and technologies in the total investment in energy technologies over the past decade. Multiplying these two vectors gave us the average share of each source per technology, such that

$$x_m^n \equiv \frac{\sum_T I_t^n}{\sum_N \sum_T I_t^n} \times \frac{\sum_T I_t^m}{\sum_M \sum_T I_t^m} \tag{2}$$

where T spans the 2006–2016 period in our data, and the coefficients add up to 1 and ensure a stable distribution of investments per technology over financing sources.

With these coefficients, we can compute the projected financing mix demanded in any scenario, provided that a scenario yields an $N \times 1$ column vector of investments, $I_{t+1\dots T}^n$. We illustrate this process in the next section for a selected set of models and scenarios.

4. From investment by technology to investment by source

As the starting point of our analysis, we took different scenarios for projected annual investment sums per technology, defined in five-year increments for the 2020–2050 period. We used the study conducted by McCollum et al. (2018) as our reference point. For illustration purposes, in this section, we focus on the scenarios produced by the REMIND-MAgPIE IAM (see McCollum et al., 2018). More scenarios based on the same study are considered in Appendix A.1. In Table 1, investments in the transformational 2 °C and 1.5 °C pathways are significantly higher than what countries are currently investing and higher than their previous policy commitments (C. Pol and NDC). REMIND-MAgPIE relies heavily on solar and wind technologies to decarbonize the power sector. Investments in solar power would thus reach 1.5 USDtn in 2050 in the 1.5 °C scenario. This begs the question of where the money would eventually come from.

We obtained the financing mix for the technologies mentioned above from historical data based on the BNEF database, which contains new investments per clean energy technology and new investment per source (see Appendix A.2). The BNEF database is the most comprehensive financing database on clean energy (Criscuolo and Menon, 2015; Eyraud et al., 2013; Polzin et al., 2015). Major investments include solar and wind power, of which a large share is financed by institutional investors and lenders through project finance, the importance of which has been growing over the last decade (see also Steffen, 2018). The BNEF offers data on 7 technologies for 10 years and, importantly,

[1] Aggregated investments over time (Source: Frankfurt School-UNEP Collaborating Centre for Climate & Sustainable Energy Finance and Bloomberg New Energy Finance (BNEF), Global Trends in Renewable Energy Investment 2017 (Frankfurt: April 2017), pp. 32–33)

Table 1
Average annual investment needs per technology across four different scenarios. Model: REMIND MAgPIE (in USDbn [billions]).

Technology	Scenarios	2020	2030	2040	2050
Bioenergy	C. Pol	5.97	0.02	0.21	0.55
	NDC	5.97	0.02	0.28	0.50
	2 °C	5.97	0.30	0.02	0.36
	1.5 °C	5.97	13.52	19.92	12.02
Hydro	C. Pol	160.99	106.22	87.63	94.52
	NDC	160.99	136.19	114.91	104.61
	2 °C	160.99	222.10	134.02	59.66
	1.5 °C	160.99	241.95	86.55	28.05
Solar	C. Pol	132.65	248.96	478.41	685.50
	NDC	132.65	331.06	563.50	742.19
	2 °C	132.65	728.93	924.75	927.34
	1.5 °C	132.65	959.52	1400.93	1482.29
Wind	C. Pol	104.80	140.47	224.60	332.04
	NDC	104.80	186.61	287.64	387.31
	2 °C	104.80	344.83	449.97	486.30
	1.5 °C	104.80	388.06	405.67	377.49

differentiates between 8 financing sources (see Appendix A.3). First, technology research (public and private R&D) usually comes in the form of a grant. Second, commercialization of a technology can be financed by venture capital (early-stage investors invest institutional money into a portfolio of start-ups). The last two forms of corporate finance that BNEF distinguishes are private equity expansion capital and public equity financing raised by established firms. Project finance (asset finance, re-invested equity) refers to a financing construction for an independent legal entity deploying a technology, usually in the form of a wind park or solar power plant. Finally, small and distributed capacity includes households (through, for example, mortgages, leasing constructions, or crowdfunding arrangements for community energy). For a review and discussion of these different sources of finance, see Polzin and Sanders (2020).

To transform the investments by source and investments by technology into a matrix of coefficients for investments by source and technology, we first took the five-year rolling averages of investments (2006–2010, 2007–2011, etc.) per source and the five-year rolling average investments per technology. The calculations used to obtain this data are included in Appendices A.4 and A.5. We conducted a series of sensitivity analyses to determine whether the length of the rolling window influences the shares of the different sources of finance (see Appendix A.5). The standard deviation of the source components ranged from 0.0007 (government R&D) to 0.0077 (asset finance). We can therefore conclude that the financing mix remained more or less stable over the 2006–2016 period. To compute our coefficients, we selected the most recent window (2012–2016). We multiplied the average share of technology n in total average investment in 2012–2016 by the average share of source m in total average investment over the same period for all n and m. Multiplying these shares resulted in the N×M matrix of coefficients (x_m^n), as seen in Table 2. This matrix can be used to map any N×1 vector of investments by technology into an N×M matrix of investment needs that can be aggregated by source.

In a third step, we used the coefficients to calculate the investment needs per source m based on the investment needs per technology n simply by multiplying (x_m^n) with ($I_{t+1\ldots T}^n$). Table 3 contains the projected totals per source and technology for the same scenarios shown in Table 1. To improve readability, the table displays only the projected investments for 2030. These numbers specify the sources of finance for the global energy transition in the power sector across the four major

Table 3
Projected investments for 2030 per source for major renewable energy technologies across four scenarios. Model: REMIND-MAgPIE (2015 USDbn).

Government R&D	C. Pol	NDC	2 °C	1.5 °C
Bio-energy	0.00	0.00	0.01	0.24
Hydropower	1.90	2.44	3.98	4.33
Solar power	4.46	5.93	13.06	17.19
Wind power	2.52	3.34	6.18	6.95
Corporate R&D	**C. Pol**	**NDC**	**2 °C**	**1.5 °C**
Bio-energy	0.00	0.00	0.00	0.19
Hydropower	1.47	1.89	3.07	3.35
Solar power	3.45	4.58	10.09	13.28
Wind power	1.94	2.58	4.77	5.37
Private Equity	**C. Pol**	**NDC**	**2 °C**	**1.5 °C**
Bio-energy	0.00	0.00	0.00	0.16
Hydropower	1.26	1.62	2.64	2.88
Solar power	2.96	3.94	8.68	11.43
Wind power	1.67	2.22	4.11	4.62
Public Markets	**C. Pol**	**NDC**	**2 °C**	**1.5 °C**
Bio-energy	0.00	0.00	0.01	0.50
Hydropower	3.90	5.00	8.16	8.89
Solar power	9.14	12.16	26.77	35.24
Wind power	5.16	6.85	12.66	14.25
Asset Finance	**C. Pol**	**NDC**	**2 °C**	**1.5 °C**
Bio-energy	0.01	0.01	0.21	9.47
Hydropower	74.37	95.35	155.49	169.39
Solar power	174.30	231.78	510.33	671.77
Wind power	98.34	130.65	241.42	271.68
Reinvested equity	**C. Pol**	**NDC**	**2 °C**	**1.5 °C**
Bio-energy	0.00	0.00	0.00	0.16
Hydropower	1.24	1.59	2.60	2.83
Solar power	2.91	3.87	8.53	11.22
Wind power	1.64	2.18	4.03	4.54
Small Distributed Capacity	**C. Pol**	**NDC**	**2 °C**	**1.5 °C**
Bio-energy	0.00	0.00	0.06	2.81
Hydropower	22.07	28.30	46.15	50.28
Solar power	51.73	68.79	151.47	199.39
Wind power	29.19	38.78	71.66	80.64

For other models incorporated by McCollum et al. (2018), the calculations can be found in Appendix A.6.

Table 2
Share of investments per source per technology (based on the rolling average of 2012–2016).

	Solar power	Wind power	Bio-power	Hydropower	Bio fuels	Geo thermal	Ocean energy	Total
Government R&D	0.0093	0.007	0.0007	0.0003	0.0003	0.0002	0	0.0179
Corporate R&D	0.0072	0.0054	0.0005	0.0003	0.0003	0.0001	0	0.0138
Venture capital	0.0028	0.0021	0.0002	0.0001	0.0001	0.0001	0	0.0053
Private equity	0.0035	0.0026	0.0003	0.0001	0.0001	0.0001	0	0.0066
Public markets	0.0191	0.0144	0.0014	0.0007	0.0007	0.0004	0	0.0367
Asset finance	0.3649	0.2747	0.0274	0.0134	0.0125	0.0066	0.0007	0.7001
(*Re*-invested equity)	0.0061	0.0046	0.0005	0.0002	0.0002	0.0001	0	0.0117
Small distributed capacity	0.1083	0.0815	0.0081	0.004	0.0037	0.002	0.0002	0.2078
Total	0.5212	0.3923	0.0391	0.0192	0.0178	0.0095	0.0009	1

technologies that feature most prominently in the REMIND-MAgPIE model (the numbers for other models and technologies can be found in Appendix A.6). Our first approximations indicated that to achieve the 2 °C and 1.5 °C pathways, some 56–70 USDbn needs to be mobilized annually by 2030 in the form of public and private R&D and private equity to finance technology development and commercialization (upstream finance). For deployment, our analysis showed that some 47–58 USDbn need to come in the form of listed equity investments (e.g., utilities). The largest amounts need to be financed through project finance. Between 907 and 1122 USDbn will need to come from institutional investors (e.g., pension funds or insurance companies). In addition to these big tickets, small and distributed finance is projected to have to play a significant role in downstream (deployment) finance—270 USDbn (2 °C) and 333 USDbn in the case of a 1.5 °C trajectory.

From our analysis of these scenarios in this IAM, it is apparent that mature technologies such as hydropower need little investment "upstream" (i.e., in government and private R&D or venture capital). On the other hand, for wind and solar power, significant upstream investments are needed to further bring down technology costs alongside deployment investments that are financed by asset finance and small and distributed capacity (Fig. 2). These projections are scenario- and model-specific. When we compare the outcomes of the REMIND-MAgPIE model with projections by the International Energy Agency (IEA-IRENA), for example, we find that the former puts more emphasis on bio-energy and wind and proportionally less emphasis on solar investments (see Creutzig et al., 2017 for a discussion regarding different estimates for solar PV). The required asset finance investments for bio-energy in these projections are typically harder to mobilize, as these technologies are not easily scaled up (Best, 2017).

However, across models and scenarios, we can conclude that asset finance for mature RE technologies such as wind (onshore/offshore) and solar PV will dominate financing needs, at least quantitatively. This is in line with findings from earlier work (Steffen, 2018). Institutional investors, who typically supply the required low-risk, large-ticket, long-term finance, have sufficient financial capacity to engage (Ameli et al., 2019; Polzin and Sanders, 2020; Röttgers et al., 2018); however, to date, regulatory and institutional barriers have prevented them from doing so at the required level. Finance for the early stages also requires significant RD&D efforts as well as venture capital. These sources are not readily available or scalable in most OECD countries, except for the Anglo-Saxon economies (US/UK) (Nanda et al., 2013; Owen et al., 2018; Polzin et al., 2017). Finally, the numbers indicate the important role that small-scale financing via crowdfunding and other household investments can play, not only in developing countries for renewable off-grid solutions (Malhotra et al., 2017) but also in developed countries (Curtin et al., 2017; Lam and Law, 2016; Vasileiadou et al., 2016).

5. Learning and dynamics in finance

As an initial approximation, we have assumed the financing mix of RE technologies to be time-invariant. That is, the composition of the portfolio of projects in each energy technology more or less stays stable over the life cycle stages and thus requires a stable mix of financing sources. In this section, we propose a theory and some initial evidence that systematically links the dynamics in the financing mix to the stage in which the technology currently finds itself on the global learning curve. We then speculate on how that might affect the shifting emphasis on financing needs and corresponding financing conditions (Egli et al., 2018; Nemet, 2006). Pan and Köhler (2007) proposed a stylized technology learning curve that can be divided into four phases. Phase I indicates the pre-production/pre-deployment phase. Phase II refers to the initial deployment characterized by a rapid reduction in technology costs, which levels off in Phase III. Phase IV depicts a fully mature technology (Fig. 3).

Using data on their installation and levelized cost of electricity (LCOE) taken from IRENA, we first gauged the life cycle stage for the major electricity generation technologies (see Fig. 4). This report on energy generation costs aims to offer representative average LCOE on the global scale, with regional data available for select technologies. We see that only wind onshore and solar PV technologies followed something like the standard learning curve during the 2000–2018 period (see Fig. 4). Based on other sources (Skoczkowski et al., 2019), we can deduce that onshore wind is currently in the later stages of technology

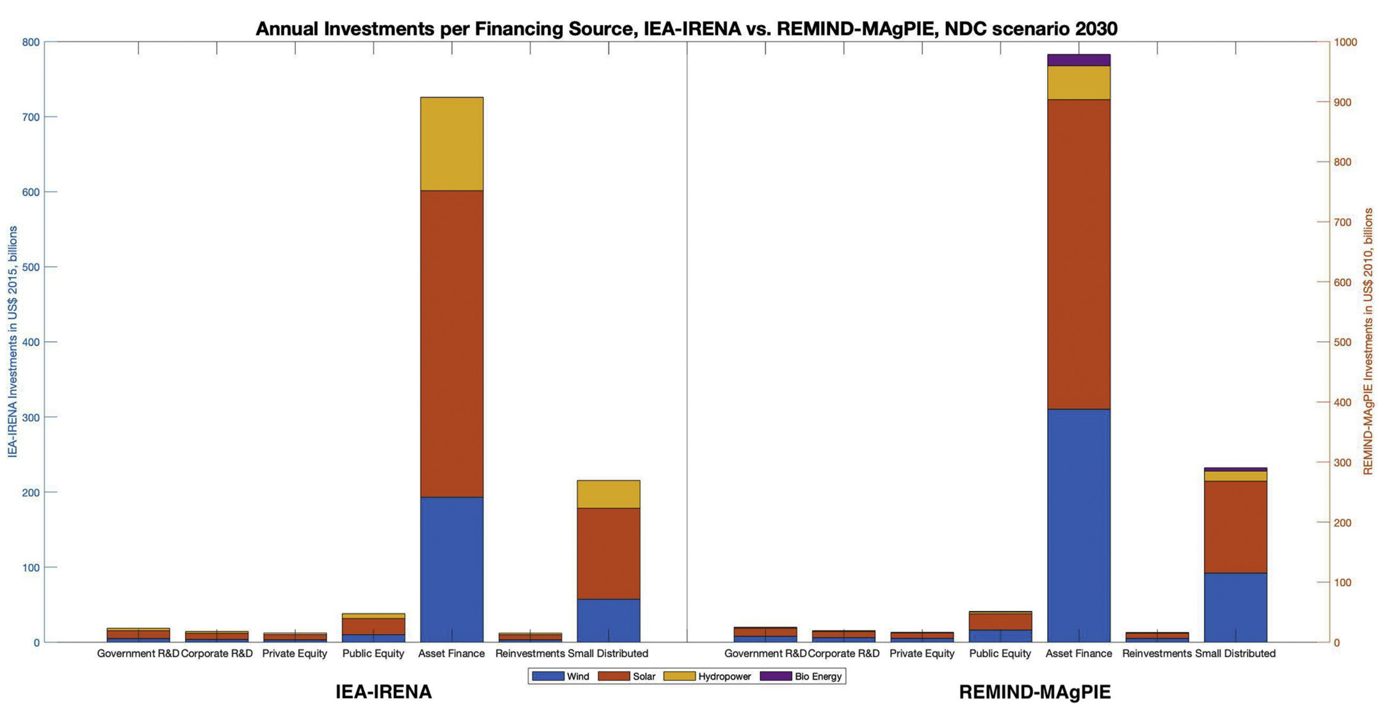

Fig. 2. Annual investment per technology, Remind-MAgPIE vs. IRENA, 2020–2050.

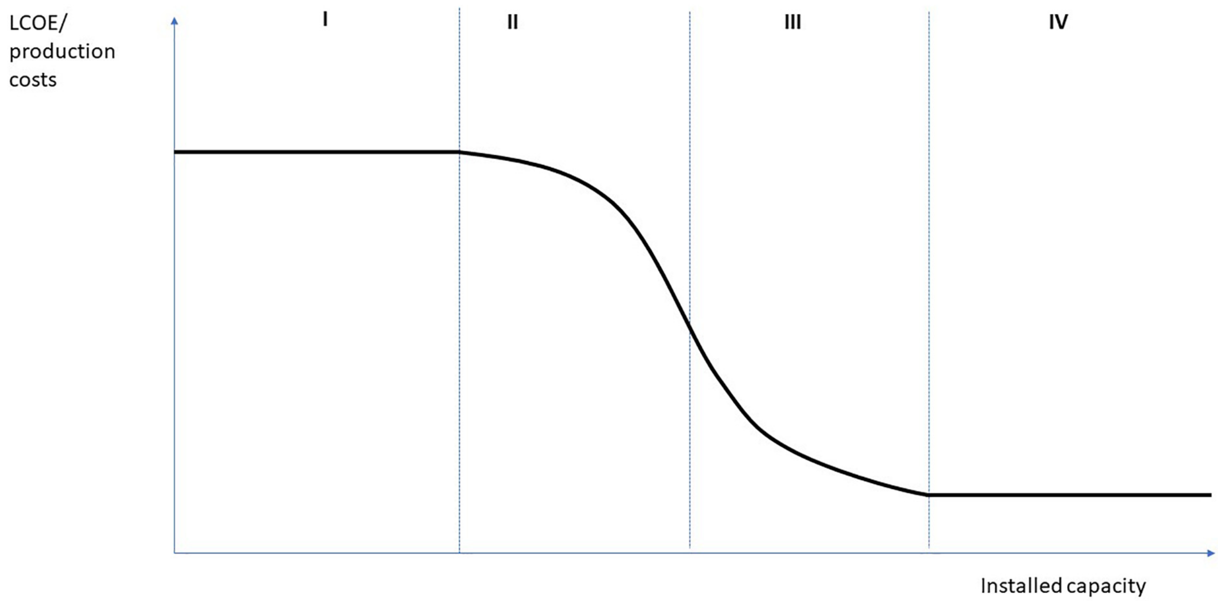

Fig. 3. A stylized logistic learning curve (based on Pan and Köhler, 2007).

development (Phase IV in Fig. 3), whereas solar PV (Phase II/III) and especially offshore wind and concentrated solar power are still experiencing significant reductions in LCOE (Phase I/II). Hydropower has been around for centuries and is extensively deployed worldwide. That is why it should be considered in Phase IV of the life cycle. Fig. 4 also shows that biomass and geothermal technologies have low LCOEs. Regarding the latter, the lack of diffusion signals low scalability and almost no technological and financial learning, corresponding to Phase I in Fig. 3. Future cost reductions are highly uncertain and as of now do not follow deployment. This may also reflect the problems of scalability and strong dependence of individual projects on local conditions. The case of biomass is harder to classify, as dedicated biomass installations still have higher costs and could be considered an early stage, whereas the co-firing of biomass in existing coal-fired power plants has much lower LCOE but also little scope for learning.

From eyeballing the data and in line with prior research (Rubin et al., 2015; Skoczkowski et al., 2019), we can classify the most important energy production technologies by life cycle stage. Table 4 summarizes our

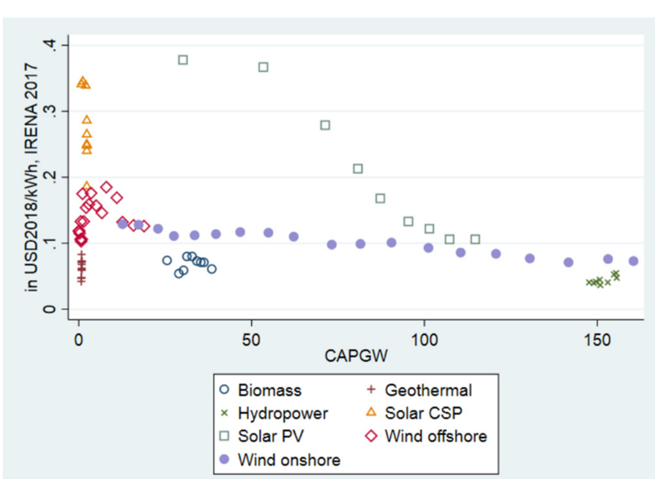

Fig. 4. Installed capacity and LCOE for major electricity generation technologies (Source: IRENA RENEWABLE POWER GENERATION COSTS IN 2018).

estimates. Most of the technologies that are broadly deployed across models and scenarios are mature ones (e.g., solar PV, wind onshore, and hydropower).

The technological learning curve is meaningfully connected to the financing mix, and falling LCOE can be an indicator for technological as well as financial learning (Egli et al., 2018; Nemet, 2006). To see changes in the financing mix for these technologies over time, we computed the difference in shares of sources of finance between 2008 and 2014 (the first and last midpoints of our five-year rolling window averages) and listed the results in Fig. 5 (the standard deviations of all rolling averages per technology are in brackets). Confirming the shift in life cycle financing depicted in Polzin et al. (2017) and others, we observe a significant increase in project/asset finance for solar PV in the decade that it shifts between Phases II and III of its life cycle. Wind has a more or less stable share of asset finance (slight changes potentially due to maturing of offshore wind technologies currently in Stages I/II). Bio energy, biofuels, and hydropower show a small decrease in the importance of asset finance, which points towards lower deployment in general.

Equity financing through venture capital or private equity stays more or less constant. Less equity financing and more project/asset finance that includes aggregated debt/equity ratios of 70/30—or 90/10 in developed economies—indicate that knowledge about RE technologies diffuses, uncertainty is reduced, and more risk-averse investors engage (Egli et al., 2018; Steffen, 2018). These learning dynamics are frequently implicitly or explicitly introduced in energy transition scenarios, though to date, they are only used in terms of reducing the LCOE over time or with installed capacity and cumulative production. We propose that linking technological learning to the dynamic

Table 4
Aggregate maturity of entire technology (portfolio of projects at different life cycle stages).

Technology	Life cycle stage
Solar PV	II/III
Wind onshore	IV
Wind offshore	I/II
Biomass	I
Geothermal	I
Hydropower	IV
Ocean	I

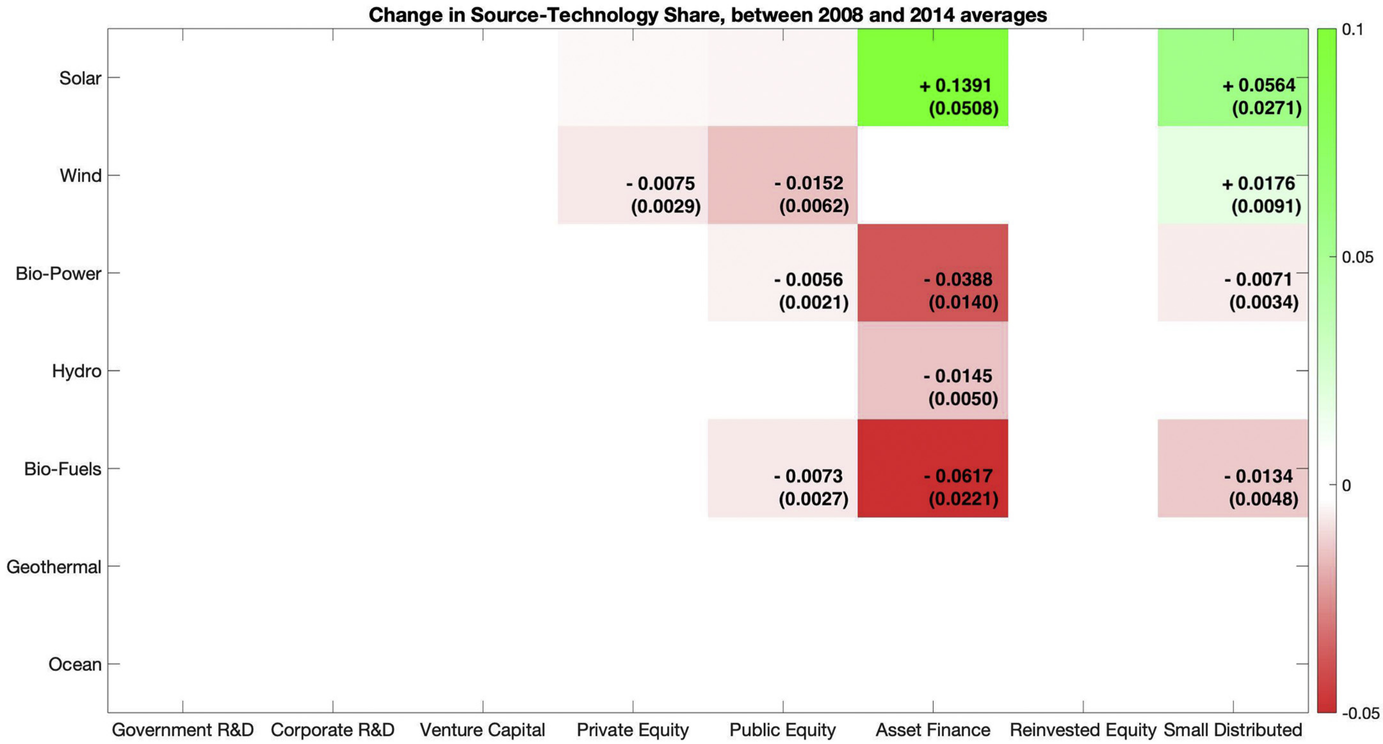

Fig. 5. Changes in financing mix over time in percent point; green represents an increase and red a decrease in importance. The standard deviation is shown between brackets. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

evolution of the financing mix can provide more accurate projections of the required financing mix in energy transition scenarios.

To analytically solve the determination of the life cycle stage and establish a rough approximation, we needed to connect the required funding mix to the life cycle stage of a technology/industry and aggregate this over industries and technologies at different moments in time. Estimating the standard learning curve (e.g. Pan and Köhler, 2007) takes the following form:

$$c_t^n = c_0\left(\sum_{\tau=0}^{t} y_\tau^n\right)^{-b} \tag{3}$$

where y_t^n is the production of power using technology n at time t, and c is the corresponding per unit cost (LCOE). We can estimate parameter b by using a dataset containing LCOE and production for time t for a set of technologies n and the regression model, as seen in

$$ln\, c_t^n = \alpha - \beta ln\left(\sum_{\tau=0}^{t} y_\tau^n\right) + \epsilon_t \tag{4}$$

After obtaining the estimated coefficients, we can compute the indicator for the life cycle stage of a technology as a function of the estimated parameters and (projected) cumulative output:

$$s_t^N \equiv \frac{1}{\left|-e^{\alpha}\beta\left(\sum_{\tau=0}^{t} y_\tau^N\right)^{-\beta-1}\right|} \tag{5}$$

where s_t^N is the inverse of the absolute value of the slope of the learning curve (the derivative of [3] with respect to cumulative production). This number takes a value between 0 and infinity and increases with cumulative production. It has no cardinal interpretation or scale but is an index that captures the life cycle stage of technology n at time t. Using projected (cumulative) production of a technology, this number can also be computed for the future in transition scenarios, adding an endogenous index for the life cycle stage per technology over time to the scenario output. That life cycle stage index can then be allowed to *change* the mix over financing sources for given energy production technologies. Of course, before we proceed with such analyses, we need to link the financing mix to the changing composition of portfolios of projects in RE technologies. At this stage, such empirically validated linkages are, to the best of our knowledge, not available in the literature and cannot be constructed with the aggregated data available to us. Access to data, on the financing mix of individual projects across renewable technologies would enable researchers to develop this research line further.

6. Conclusions and implications

To the best of our knowledge, this is the first attempt to estimate financing needs by source for the global energy transition. We show that while significant amounts of resources need to be committed to deploying RE by institutional investors, private households also have a significant role to play. In addition, governments and private companies innovating in the RE space need to expand their investments in novel and improved technologies to keep the energy transition going. The main contribution of this paper, as we see it, is a proposed method for mapping scenario projections of required investments per technology into a demand for financial resources per source. Based on such projections, policy makers can begin to target specific types of investors with policy measures. To date, policy makers lack such information, and based on the transition scenarios that scientists provide, they can only make policies by setting ambitious emission reduction goals that, if investment does not follow scenario projections, will be missed. Translating projected investment needs per technology into a required financial mix gives policy makers an actionable agenda for enabling the transition using the financial market as the focal point (Polzin et al., 2019).

Our analysis highlights the importance of asset finance, as it can finance the largest proportion of investment needed in the most promising renewable technologies: wind and solar power. The REMIND-MAgPIE scenario, corresponding with 2 °C of warming, requires USDbn 340 in wind and USDbn 650 in solar in annual investments by 2050 from asset finance. Such investment amounts require facilitating a large, stable, and competitive financial market for RE, particularly with risk-averse institutional investors. Uncertainties in terms of subsidies and market prices can greatly impact these investors (Egli, 2020). Policies should therefore be designed such that any changes are well-communicated, phased in gradually, and not applied retroactively (Polzin et al., 2019). Guaranteed grid connection for new renewable plants is another suitable option for reducing risk. In addition, policy makers could relax regulations to allow institutional investors, such as pension and sovereign wealth funds, to invest in long-term, stable cash flow but low liquidity, unlisted projects in the RE and energy efficiency sectors.

Creating standardized deal structures and project evaluation across investor types and sectors would also help bring a volume and diversity of investors into the market. This includes small-scale, distributed investors, who were also highlighted as a key source of finance in our analysis. Specifically, standardization decreases barriers to entry, as technical and legal expertise does not have to be kept in-house in order to internalize risk. Investors with debt overhang and many new project finance vehicles, such as independent developers and citizen co-operatives, would particularly benefit from this (Steffen, 2018).

Another policy structure that would aid particularly risk-averse institutional investors and smaller financial actors with little technological expertise is to improve disclosure standards in the EU taxonomy for sustainable economic activities. Two new regulatory benchmarks, “Climate Transition” and “Paris-aligned,” were put forth to allow investors to compare the carbon impact of their investments in a systematic way (European Parliament, 2019). This would aid different financial actors in structuring their portfolios in a manner more consistent with environmental, social and governance standards—not just with a vague low-carbon mandate, but in direct alignment with the Paris Agreement goals of limiting climate change to well below 2 °C of warming. Benchmarks are especially useful to institutional investors, with pension funds being a primary user of the lighter “Climate Transition” framework (TEG, 2019). The requirement that all financial assets issued within the EU are evaluated for benchmark compliance is therefore useful.

As is clear from our analysis, the proposed method in this paper is limited by the lack of data on RE investment projects per source and technology, or even at the project level. BNEF could make this data available to advance future research efforts. Even historical data would be useful for estimating the link between life cycle stages and their corresponding financing mixes. To help policy makers target the scarce public resources available for pushing the energy transition in the years to come, such data must be collected systematically and used to improve the coefficient matrix, create the dynamic dimension based on technological life cycles, and map projected investment volumes into more precise and reliable financial resource needs.

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Appendix A. Supplementary data

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