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Picking Winners: technology-specific policies can be welfare improving

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I show that the commonly held belief that policy should not pick winners is not always valid. Picking winners can increase social welfare above the decentralized equilibrium even when the policymaker has no exclusive knowledge of which technologies are most viable, and even when the market has private information unavailable to the policymaker. Innovation requires the use of scarce resources to bring a new product to market and improve the quality of existing products. Product redundancy, where the improvement of a product's value comes partly at the expense of substitute products, reduces the incremental value of additional products. When the number of products in the market is endogenous, there exists a tension between the benefits of developing a larger suite of technologies and the benefits of allocating more innovative resources towards each technology developed. Product redundancy in conjunction with product innovation can lead to the market developing more products than is socially optimal. A policy which selects a subset of technology options to support–picking winners–can increase social welfare. The results of this paper contribute to the ongoing discussion of industrial policy and are of particular importance for policies aimed at mitigating climate change.

A commonly held belief is that policy should not "pick winners" but should instead allow market forces to decide how resources are allocated (Aghion et al., 2011, 2015; Nathan and Overman, 2013; Rosenberg, 1998; Schultze, 1983). The aversion to picking winners is used as an argument against targeted research

(Rosenberg, 1998), enforced standardization, or industrial policy (Aghion et al., 2011). It is assumed that "targeted subsidies to specific types of research" leads to wastage "because of the inefficiency of picking winners" (Acemoglu et al., 2016). Even when a class of technologies is socially preferred, such as with clean versus dirty technologies, the assumed optimal policy supports a broad sector and is "not biased towards individual firms within the sector" (Aghion et al., 2011).

I show that picking winners can increase social welfare above the decentralized equilibrium even when the policymaker has no exclusive knowledge of which technologies are most viable, and even when the market has private information unavailable to the policymaker. A social planner balances the benefits of developing a larger suite of technologies with the benefits of allocating more scarce resources towards each technology developed. New technologies produce new products, and the value of introducing a new product partially comes at the expense of lower utilization of substitute products. Because substitute products are partially redundant, the social value of a new product is less than the private value generated by that product. Product redundancy combined with innovation in new technologies results in the decentralized equilibrium developing more technologies, with less resources devoted to innovating each technology developed, than is socially optimal. A policy which supports a subset of technology options–picking winners–can increase social welfare.

Product redundancy due to competition between substitute products is part of a well functioning market and is not a market failure. Innovation in new technologies is not a cause for market intervention either. It is the fact that technology innovation makes the number of products endogenous, working in conjunction with product redundancy, which can result in the market solution deviating from the social optimal. Thus, while product redundancy and product innovations alone do not warrant technology-specific policies, the combination of the two can result in technology-specific policies being welfare improving.

The negative view of picking winners largely stems from the fact that policymakers often do not have the information needed to determine which potential innovations are most viable (Nathan and Overman, 2013; Owen, 2012; Rosenberg, 1998). Uncertainty in the innovation process means winners are difficult to predict, so picking a particular technology or particular path is likely to result in failure (Owen, 2012). The argument against picking winners is well summarized by the words of Rosenberg (1998):

> The pervasiveness of uncertainty suggests that the government ordinarily should resist the temptation to play the role of a champion of any one technological alternative, such as nuclear power, or any narrowly concentrated focus of research support, such as the "War on Cancer." Rather, it would seem to make a great deal of sense to manage a deliberately diversified research portfolio...In fact, a considerable virtue of the marketplace is that, in the face of huge ex-ante uncertainties concerning the uses of new technological capabilities, it encourages exploration along a wide variety of alternative paths.

Policymakers often face the problem of determining how to allocate scarce resources towards a portfolio of potential options such as technologies, projects, or industries. The belief in not picking winners has significant policy implications for such circumstances–namely, defer to the market's decision of which options to support. As this paper shows, however, the market does not always correctly balance the tension between the benefits of developing more technologies and the benefits of allocating more resources to each technology developed. This can result in innovation in too many technologies at a level of innovation than is lower than socially optimal. Picking winners, supporting a subset of technologies, can therefore be welfare enhancing.

Choosing the "right" number of options to pursue is especially important when allocating resources towards research and development. Dasgupta and Maskin (1987) list how many and what kinds of options to pursue as among the major questions in the economics of science and technology.[1] For many important problems there is no technology which currently offers an adequate solution, but instead there are an array of technologies which, with additional research and development, could contribute to the solution. Early stages of development are marked by a plethora of competing options, large uncertainty over the relative merits of each option, and additional resources required to develop each option.

The modeling framework of this paper has several connections to the economic growth literature, such as Schumpeterian models with product diversity (Akcigit and Kerr, 2018; Howitt, 1999; Young, 1998), and models of semi-endogenous growth (Jones, 1995; Kortum, 1997; Segerstrom, 1998). The results of this paper connect to the broader literature of innovation and the role of government, and contributes to the ongoing debate on the merits of industrial policy.

Selective government intervention, often referred to as industrial policy, is one of the most contested topics in economics. Critics argue that the government cannot pick winners and may end up picking losers (Klimenko, 2004; Krueger, 2011; Pack and Saggi, 2006; Schultze, 1983). Proponents of industrial policy cite a variety of market imperfections which call for government intervention such as imperfect competition (Aghion et al., 2015), coordination failures between sectors (Greenwald and Stiglitz, 2013; Rodrik, 2004), knowledge spillovers (Lin, 2012; Rodrik, 2014; Stiglitz et al., 2013), information asymmetries (Cohen, 2006; Rodrik,

[1]The major questions in the economics of science and technology according to Dasgupta and Maskin (1987) are:

> (1) What problems ought to be on the agenda? (2) How many and what kinds of research projects (or research strategies) ought to be pursued in tackling them? (3) How ought resources to be allocated among the chosen research projects? (4) Who ought to be conducting the research? and (5) How ought research personnel to be compensated?

2009), and environmental externalities (Aghion et al., 2011; Rodrik, 2014). But even proponents readily admit the picking winners counter-argument (Greenwald and Stiglitz, 2013; Rodrik, 2004). Those in favor of industrial policy recommend government policies that support sectors with the most positive spillovers and shift support away from sectors with negative spillovers; with papers such as Liu (2019) and Hausmann et al. (2008) suggesting methods for how sectors could be ranked.

This paper contributes to the literature by showing the targeting of specific firms, technologies, or sectors can increase welfare when there is both innovation to develop new products and product redundancy from substitute products. This suggests a policy of picking winners in markets where products are close substitutes and significant innovation in new products is present. Additionally, I discuss how policy intervention in such markets can be welfare improving even when decentralized actors have private information unavailable to the policymaker.

The results of this paper are of particular importance for policies aimed at mitigating climate change. Innovation in clean technologies has a large impact on the total damages caused by climate change (Acemoglu et al., 2012, 2016; Barrett, 2006; Goulder and Mathai, 2010). A large suite of potential technologies can lower emissions, but there are limited resources which can be devoted towards the research and development of these clean technologies (Pless et al., 2020). Finding the correct balance between the number of technologies to support and the amount of resources to devote to each technology will provide the best chance of avoiding the worst effects of climate change.

Section I develops the primary insight that product redundancy in conjunction with innovation in new products can lead to the market developing more products than is socially optimal, and that it can be welfare improving for a policymaker to pick winners to reduce product overlap. Section II considers the case where the market has private information unavailable to the planner. I show that it still may be optimal for the planner to pick winners, and that a policy instrument such as a tax or quota on the number of technologies developed can be welfare improving. Section III discusses the policy implications of the results.

I. General Framework

I consider a market which is served by a continuum of products, where for each product there is a unique technology used to produce it.[2] The relevant distinction between technologies and products is that a technology impacts the cost and quality of production while a product is consumed by end customers. All technologies are immature and require additional research to bring their associated product to market. Following Aghion and Howitt (1992) and Acemoglu et al. (2012), I model research and development resources as a limited number of scientists who can undertake innovative activities; with the number of scientists normalized to one. It is worth noting that modeling scientific resources as unconstrained but costly–with a fixed wage rate to hire scientists–leads to equivalent results.

Let $v(i, n, s_n(i))$ denote the value of product $i \in [0, n]$, where $n \in [0, N]$ iss the number of products developed from a pool of $N \in \mathcal{R}$ possible products, and v is a bounded continuous function. $s_n(i)$ denotes the number of scientists devoted to innovating technology i given scientists are allocated between the n technologies developed. The budget constraint on scientists can be expressed as:

$$\int_0^n s_n(i)di = 1 \tag{1}$$

Each technology requires innovation to enter the market, so $v(i, n, 0) = 0$. Innovation, which occurs when scientists work on a given technology, can lower

[2]While it may be more natural to think of a discrete number of product options, the assumption of continuity provides cleaner results, and having a discrete number of products does not lead to qualitative differences.

the cost of production or increase the quality of the associated product. More scientists lead to more innovation, so $v(i, n, s_n(i))$ is increasing in $s_n(i)$. However, there are diminishing returns in the productivity of scientists. This is due to duplicate discoveries (Hill and Stein, 2019; Merton, 1961, 1968; Stephan, 1996), approaches to innovation being substitutes for each other (Bloom et al., 2013), and the fact that innovation expands the technological frontier making new discoveries harder to find (Bloom et al., 2017; Kortum, 1997; Porter and Stern, 2000), which results in diminishing returns to research effort at any given time and across time (Fischer and Newell, 2008; Popp, 2004).

The value of each product is decreasing in the number of competing products, $v(i, n, \bar{s}_i)$ is decreasing in n. A new product increases welfare more when there are few competing products than when there are a plethora of competing products. A new medicine that treats a previously untreatable disease benefits society more than if the medicine merely offers a new way to treat the disease. A new way to produce clean energy is more valuable when generation from wind and solar is expensive than when they are cheap. Kogan et al. (2017) estimates a substantial degree of market-share stealing, finding a one standard deviation increase in competitor innovations reduces a firm's output by 5.1% and capital investment by 3.8%. Similarly, Bloom et al. (2013) discusses the negative "product market rivalry effect" of R&D used to steal market share from competitors. More products available leads to more redundancy between products (Yang and Heijdra, 1993), and innovation in one technology leads to reduced use in substitute technologies (Kogan et al., 2017).

Products can differ in usefulness to the end consumers, and technologies can vary with respect to factors such as current level of maturity, likelihood of successful innovation, and potential benefits from innovation. I assume technologies are ordered by viability such that it is optimal to begin developing lower numbered technologies before higher numbered technologies. Mathematically, I assume $v(n, i, s) \geq v(n, j, s)$ for all $i < j$. This ordering captures ex-ante knowledge of expected viability and does not have to equate to the ex-post value of each product which is unknown due to the innovation being inherently uncertain.

Total social value is given by:

$$V(n, s_n) = \int_0^n v(i, n, s_n(i))di - F * n \tag{2}$$

where F is a (potentially zero) fixed cost of developing a new technology and F is small enough that it is welfare improving to innovate in at least some technologies.

I now determine the socially optimal number of technologies, the optimal allocation of scientists, and how a decentralized equilibrium differs from the optimal allocation.

A. Social Planner's Problem

A social planner chooses the number of products and allocation of scientists to maximize total welfare (2) subject to the scientist resource constraint (1). I first determine the optimal allocation of scientists for a fixed number of technologies $\bar{n}$. Assuming v_s exists and is continuous with respect ot i and s, then we can write the Gateaux differential with increment h as:

$$\partial V(\bar{n}, s_{\bar{n}}; h_{\bar{n}}) = \int_0^{\bar{n}} v_s(i, \bar{n}, s_{\bar{n}(i)})h_{\bar{n}}(i)di \tag{3}$$

At the optimal allocation $s^*_{\bar{n}}$ there is no valid reallocation of scientists between the $\bar{n}$ technologies which increases welfare (Luenberger, 1997). Therefore, for any $i \leq n$, $v_s(n, i, s^*_{\bar{n}}(i)) = v_s(0, n, s^*_{\bar{n}}(0))$. Letting $\lambda_{\bar{n}} = v_s(0, \bar{n}, s_{\bar{n}}(0))$, then $v_s(i, \bar{n}, s^*_{\bar{n}}(i)) = \lambda_{\bar{n}}$ for all $i \leq n$.

Letting $V(n) = V(n, s_n^*)$, then:

$$V(n) = \int_0^n v(i, n, s_n^*(i))di - F * n$$
$$V'(n) = v(n, n, s_n^*(n)) + \int_0^n v_n(i, n, s_n^*(i)) + v_s(i, n, s_n^*(i))\frac{\partial s_n^*(i)}{\partial n}di - F \tag{4}$$

As shown in Appendix **??**, if the optimal number of technologies, n^*, is less than N, then the following holds:

$$\underbrace{v(n^*, n^*, s_{n^*}^*(n^*))}_{\text{Product Value}} = \underbrace{F + \lambda_{n^*} s_{n^*}^*(n^*)}_{\text{Development Costs}} - \underbrace{\int_0^{n^*} v_n(i, n^*, s_{n^*}^*(i))di}_{\text{Product Redundancy}} \tag{5}$$

It is optimal to innovate technologies to the point where the value of the next technology equals the fixed cost of development, plus the opportunity cost of scientists not allocated to other projects, plus the opportunity cost of other products becoming partially redundant.

B. Decentralized Equilibrium

I now consider the allocation of scientists given firms hire scientists in a self-interested decentralized manner. To enter the market, firms pay a fixed cost F, and in return receive patent rights to a technology. I assume firms can extract all rents from their technology, so that revenues for the firm with the patent on technology i who hire $s_n(i)$ scientists is $v(i, n, s_n(i))$.

There is a single market for scientists, who inelastically supply labor to the market. In Appendix B I show that, given $\bar{n}$ technologies are developed, the wage rate for scientists is $\lambda_{\bar{n}}$ and the allocation of scientists to technology i is $s_{\bar{n}}^*(i)$. it is worth highlighting the fact that for a fixed number of technologies the market equilibrium allocation of scientists coincides with the planner's allocation. Thus, any difference between the planner's solution and the decentralized equilibrium are due to differences in the number of technologies developed.

Due to free entry, firms will enter until the next entrant makes zero profits. Hence, as shown in Appendix **??**, in the decentralized equilibrium $\hat{n}$ technologies are developed, where $\hat{n}$ is such that the following zero profit condition holds:

$$\underbrace{v(\hat{n}, \hat{n}, s^*_{\hat{n}}(\hat{n}))}_{\text{Product Value}} = \underbrace{F + \lambda_{\hat{n}} s^*_{\hat{n}}(\hat{n})}_{\text{Development Costs}} \tag{6}$$

C. Comparison of Social Planner Solution to Decentralized Equilibrium

The motivation to innovate in novel projects is well known to any researcher who strains to find "gaps in the literature", and the reality of product redundancy is even better understood by all who have gone to graduate school and inevitably have nightmares about discovering their research is redundant. Comparing equations (5) and (6), the social planner balances the benefits of increased product variety against both the cost of developing the new technology and the opportunity cost of making other innovations redundant. Individual firms do not internalize the opportunity cost of making other products redundant in their decision process. Therefore, the decentralized equilibrium innovates in at least as many technologies as the social planner.

If product redundancy is non-zero and the optimal developed is less than N, then the number of technologies developed in the decentralized equilibrium is greater than in the planner's solution. Additionally, Since $s^*_n(i)$ is decreasing in n, $s^*_{n^*}(i) \geq s^*_{\hat{n}}(i)\ \forall i \in [0, n^*]$.

Proposition 1. *The decentralized equilibrium develops more technologies than the social planner and the number of scientists per technology in the decentralized equilibrium is less than the social planner solution.*

Proposition 1 is a direct result of the opportunity cost of innovation lost due to product redundancy appearing in the planner solution (5) but not in the decentralized equilibrium (6). The result that more technologies are developed in the decentralized equilibrium than in the planner's solution leads directly to our next proposition, which is a central result of this paper.

Proposition 2. *Picking winners–developing less technologies than would be developed in the decentralized equilibrium–can increase social welfare.*

From Proposition 1 the number of technologies developed in the social planner solution is less than the number developed in the decentralized equilibrium. Because welfare is maximized by the social planner and the decentralized equilibrium is different from the social planner solution, welfare in the decentralized equilibrium is less than the social planner solution. Furthermore, the planner's solution can be met by supporting a subset of available technologies.

Proposition 1 holds even though the policymaker does not have exclusive knowledge of which technologies are best to support. This result highlights an additional externality caused by product redundancy when in conjunction with innovation, which results in the decentralized equilibrium differing from the planner's solution.

It is important to reiterate that these results occur when substitute products and innovation of new products are simultaneously present. Innovation in new technologies, which makes the number of products endogenous, working in conjunction with product redundancy is what can cause the market solution to deviate from the social optimal. Thus, it is not product redundancy or innovation in new products but the combination of the two which may warrant technology-specific policies.

II. Private Information

Limited knowledge from the policymaker's point of view is often brought up as to why policymakers should not pick winners. Knowledge of the viability of various technologies may be private knowledge held by individual firms or scientists. As Hayek (1945) states:

> practically every individual has some advantage over all others because he possesses unique information of which beneficial use might be made, but of which use can be made only if the decisions depending on it are left to him or are made with his active cooperation.

If decentralized actors have better information than centralized planners then the market allocation of resources may be more efficient than the centralized solution. Given product redundancies however, it may still be welfare improving for a social planner to pick winners. Furthermore, a policy which accounts for product redundancy while leveraging market information can be beneficial.

Let the expected value of product i be $v(x(i), n, s_n(i))$, where $x(i)$ is a realization of the random variable $X(i) \sim F(x; i)$ with support over $\Omega(i)$. Given development is inherently uncertain, the actual product value will likely not be known until after development takes place. Uncertainty in $x(i)$ instead captures higher-order uncertainty regarding which technologies are the most promising to develop in the first place.

I assume the $x(i)$'s are uncorrelated with each other and that v is increasing in x. Private information is incorporated by requiring the planner to make decisions before x is realized while allowing firms to make decisions after observing x.

Let $\theta(i)$ be such that:

$$v(\theta(i), n, s_n(i)) \equiv E[v(X(i), n, s_n(i))] \tag{7}$$

Let technologies be are ordered such that $\theta(i) > \theta(j)$ whenever i is less than j. Thus technology i is expected to be more viable than technology j whenever $i < j$. Because the planner chooses technologies and allocates scientists before uncertainty is revealed, the planner's problems is equivalent to that of Section I.A with the indicator i replaced by $\theta(i)$.

The planner develops n technologies, with n being determined implicitly by:

$$\begin{aligned} v(\theta(n), n, s_n(n)) &= F + s_n(n)\lambda_n - \int_0^n v_n(\theta(i), n, s_n(i))di \\ v_s(\theta(i), n, s_n(i)) &= \lambda_n \ \ \forall i \in [0, n] \end{aligned} \tag{8}$$

Decentralized firms have better information on which technologies are most promising and therefore observe each $x(i)$ before entering. While technology i is expected to be more promising than technology j whenever $i < j$, the order may be reversed once $x(i)$ and $x(j)$ are realized. Therefore, even if the planner and the market develop the same number of technologies, the technologies chosen will be different under the two solutions.

Let κ be a function which orders the realizations of x so that $\kappa(i; x)$ is the i'th highest x draw. Let $\kappa(i; x)$ converge to $\gamma(i)$ and let $\sigma_m(i)$ denote the number of scientists allocated to the $i'th$ most viable technology given m technologies are developed.

Figure 1 displays an example with $x(i)$ normally distributed around $\theta(i)$ and $\theta(i)$ decreasing linearly with n. The gray points denote x draws of. The line γ is the distribution given the x draws are reordered, which is what the decentralized market makes decisions based on.

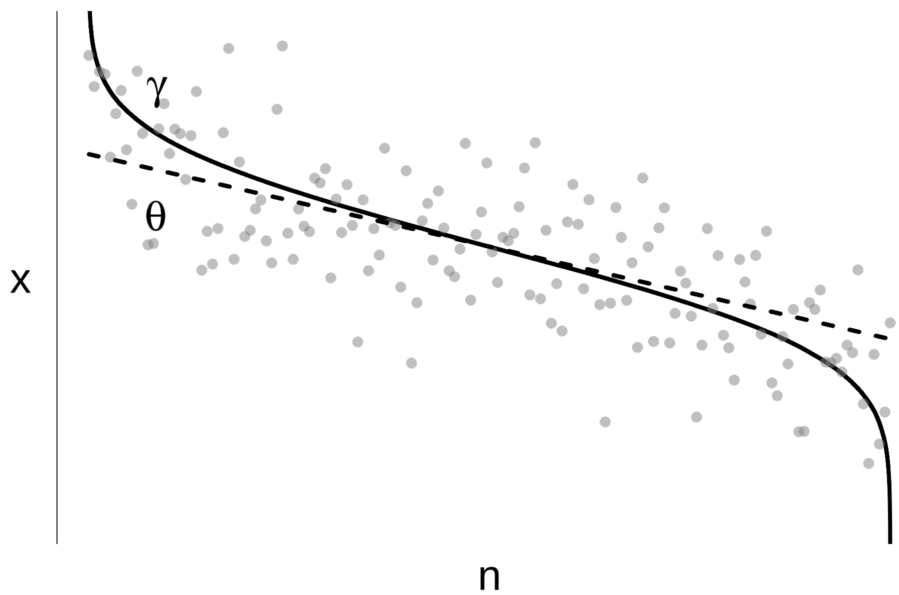

FIGURE 1. EXAMPLE REALIZATION OF x

The number of technologies developed in the decentralized equilibrium is implicitly given by:

$$\begin{aligned} v(\gamma(i), m, \sigma_m(m)) &= F + \sigma_m(m)\psi_m(x) \\ v_s(\gamma(i), m, \sigma_m(i)) &= \psi_m(x) \;\; \forall i \in [0, m] \end{aligned} \tag{9}$$

The derivation follows the same steps as in Appendix B. We cannot say whether the decentralized equilibrium develops more or less technologies than the planner. If one technology is far superior to the others then the market will only develop the superior technology while the ignorant planner has to develop several technologies to guarantee the superior technology is among them. Thus, the market can develop less technologies than the planner. The previous section gives a case where the opposite is true. We can say that a small fixed cost F, large product redundancy, and less uncertainty in x will each make it more likely that the decentralized equilibrium develops more technologies than the planner.

In the following analysis I assume the parameters are such that more technologies are developed in the market solution than in the planner's solution. As shown in Appendix C, the difference in expected welfare between the market and planner's solution is given by:

$$\begin{aligned}
&\left[\int_0^m v(\gamma(i), m, \sigma_m(i))di - mF\right] - \left[\int_0^n v(\theta(i), n, s_n(i))di - nF\right] \\
&\qquad = \underbrace{\int_0^n v(\gamma(i), n, \sigma_n(i)) - v(\theta(i), n, s_n(i))di}_{\text{Distribution Gains}} \\
&\qquad + \underbrace{\int_0^m v(\gamma(i), n, \sigma_m(i))di - \int_0^n v(\gamma(i), n, \sigma_n(i)) - F(m-n)}_{\text{Portfolio Gains}} \\
&\qquad - \underbrace{\int_0^m v(\gamma(i), n, \sigma_m(i)) - v(\gamma(i), m, \sigma_m(i))di}_{\text{Total Product Redundancy}}
\end{aligned} \tag{10}$$

Distribution gains are the gains from the market more efficiently distributing scientists given the market develops the same number of technologies as the planner. Portfolio gains are the net value of the additional technologies the market develops holding product redundancy fixed. Finally, total product redundancy is the additi9onal opportunity cost of product overlap. in the decentralized equilibrium. We can now say when a centralized solution will be preferred to the market equilibrium.

Proposition 3. *Give decentralized actors have private information, the planner's solution is still preferred to the market equilibrium if the loss from product redundancy exceeds the market distribution and portfolio gains.*

Policy Instruments

The social planner accounts for product redundancy when choosing the number of products to develop, which places her in a position to increase social welfare by choosing the number of technologies to develop. Meanwhile, decentralized actors have better on-the-ground information of which technologies to develop and how to allocate themselves towards the most viable technologies. A social planner may "pick the wrong winners" and allocate scientists inefficiently, which can result in lower welfare than the decentralized equilibrium. That both planner and scientists have valuable information to contribute suggests a policy instrument which incorporates information from both can be welfare enhancing.

The optimal policy is given by $\tilde{n}$ technologies and a distribution of scientists $\sigma_{\tilde{n}}$ such that:

$$\begin{aligned} v(\tilde{n}, \sigma_{\tilde{n}}(\tilde{n}), \gamma(\tilde{n})) &= F + \sigma_{\tilde{n}}(\tilde{n})\psi_{\tilde{n}} - \int_0^{\tilde{n}} v_n(\tilde{n}, \sigma_{\tilde{n}}(i), \gamma(i))di \\ v_s(i, \sigma_{\tilde{n}}(i), \gamma(i)) &= \psi_{\tilde{n}} \quad \forall i \in [0, \tilde{n}] \end{aligned} \tag{11}$$

Such a policy may be implemented by setting a quota on products at $\tilde{n}$ or by setting a tax of $\int_0^{\tilde{n}} v_n(\tilde{n}, \sigma_{\tilde{n}}(i), \gamma(i))di$ per product. Both policies act to reduce the number of products competing in the market and thereby reduce product redundancy.

Proposition 4. *A tax or quota on the number of products developed can reduce product redundancy and increase welfare.*

Whether a tax or quota is preferred depends on the specific case. Because the planner does not have complete information, the familiar analysis of price vs quantity policies under uncertainty applies (Weitzman, 1974).

III. Discussion and Applications

It may be difficult to envision what a tax or quota on innovative activities would look like, or why such a policy would be useful. Those familiar with the innovation literature may find it strange to even consider a tax on innovation. Innovation has clear positive spillovers which rightfully should be subsidized.

The results of Propositions 2 through 4 can best be understood in the context of a decision maker endowed with a limited budget to devote to innovative activities. Examples include the National Science Foundation allocating grants to a portfolio of research projects, the Department of Energy choosing which energy technologies to support, or the Department of Health and Human Services allocating funds to speed up the development of a vaccine. The decision maker can direct how funds are allocated or can allow market forces to decide, such as by offering subsidized loans. Private information held by decentralized actors may mean the market can more efficiently allocate resources than the planner could. Because of product redundancy however, the optimal allocation likely consists of supporting a smaller number of projects with more funding than would result from relying on market forces alone. In this case, policy instruments may be effective at leveraging market information while also accounting for project redundancy. In the context of a decision maker choosing how to allocate funds, a quota can be seen as the decision maker offering a limited number of grants, and a tax can be seen as any policy which raises the barriers to apply to or receive a grant.

The result that the market may develop more technologies than is socially optimal suggests policies which focus on a few technology options may be preferable to policies which provide an even playing field to all technologies. The NSF may be most effective by giving a smaller number of larger grants instead of a larger number of smaller grants. Instead of the "all of the above" policy the DOE currently promotes, which funds a wide array of potential energy innovations, a policy which targets research funding to a smaller number of technologies could bring about more impactful innovations; a result which is especially important given innovation in the energy sector is essential for mitigating climate change. Directing more funding, research, and clinical trial participants to a smaller number of vaccine candidates could reduce the time for an effective vaccine to reach the market.

The optimal portfolio size depends on the amount of product redundancy and the concavity of returns to scientific effort. High product redundancy and low concavity (slowly low decreasing returns) of scientific effort recommends a small portfolio, while low product redundancy and high concavity (quickly decreasing returns) of scientific effort recommends a large portfolio. Therefore, picking winners is most likely to increase welfare in the case of markets with high levels product redundancy. This insight leads to different policy recommendations for seemingly similar problems.

One example of where the results of this paper imply different policy recommendations to seemingly similar problems is with regards to policy options to reduce car emissions. Emissions from transportation is the leading contributor of greenhouse gas emissions,[3] so reducing the carbon intensity of cars is a critical step in mitigating climate change. The two means of reducing emissions from cars are to increase the fuel efficiency of gas cars and to switch to an alternative fuel source–namely electric batteries or hydrogen fuel cells.

Battery electric cars require a significant build-out of charging stations along with innovations to reduce the cost, weight, size, and charge time of batteries and increase their longevity and safety. Similarly, hydrogen fuel cells require a network of fueling stations and the associated infrastructure to support such a

[3]Transportation accounts for the largest share of greenhouse emissions of any sector, accounting for 28% of total US emissions in 2018 (EPA, 2018).

network, and require innovation to reduce costs and improve performance. A car will only use a single power source, which means that there is significant product-level redundancy between these options. A fleet of fuel cell cars would largely come at the expense of a smaller fleet of battery-electric cars.

Innovations to increase the gas mileage of cars, such as better designed engines or the use of lighter composite materials, can be incorporated into the same car and therefore largely do not conflict, and can in fact be complementary innovations. Innovations to increase fuel efficiency therefore likely have low product-level redundancy.

The low level of product redundancy between efficiency improvements suggests a policy which supports a broad range of options. Such policies may include a gas tax or fuel efficiency standards, which benefit all means of improving efficiency equally. Meanwhile, high level of redundancy between battery-electric, and hydrogen powered cars implies a policy of picking a single winner to devote research funds towards may actually be preferred to a policy of supporting each option equally.

A. Application to Winner-takes-all Market

Innovation is often modeled as a winner-takes-all market due to rights of first discovery, such as patents or recognition from publication, which lead the bulk of compensation for innovation to often go to the first to innovate (Dasgupta and Maskin, 1987; Hill and Stein, 2019; Merton, 1961; Stephan, 1996). Additionally, markets where competing products are near-perfect substitutes are often served by a single product, resulting in the most innovative technology claiming total market share. Given a winner-takes-all market is the framework commonly used when studying innovation, it is useful to see how the previous analysis relates.

In a winner-takes-all market, the most innovative product captures the entire market share. This framework also incorporates markets where the first to innovate captures the market by translating the level of innovation to speed of innovation. With perfect substitutes the best product is used, the first to make a scientific discovery get the bulk of credit, the first vaccine to complete clinical trials is likely the one distributed. Ex-ante uncertainty regarding the ex-post level of innovation can lead to multiple technologies being developed however. Because the best choice is not known ahead of time, developing several technologies increases the pool of technologies to draw from. Competing technologies are therefore not fully redundant even though only one will be used in the market. At the same time, product redundancy is clearly baked into a winner-takes-all market because the chance of a new product being the one developed decreases as competing products are added.

Let the level of innovation in technology i be given by the random variable $X(i, s_n(i)) \sim F_i(x; s)$ where $s_n(i)$ is the number of scientists devoted towards technology i. Again, the level of innovation may stand for the speed of discovery with a larger innovation denoting a quicker discovery. I assume $F(x; s)$ first-order stochastically dominates $F(x; t)$ whenever $s > t$ and $F_i(x; s)$ dominates $F_j(x; s)$ whenever $i < j$. This ensures research increases expected innovation and establishes earlier numbered technologies to be at least as viable as later numbered technologies. I assume innovation draws are uncorrelated with each other, that there are decreasing returns to innovation, and $X(0) = 0$.

Welfare is given by the expected level of innovation in the most innovative technology, minus fixed costs of development, which can be written:

$$V(n, s) = E[\max(X(1, s_n(1)), \ldots, X(n, s_n(n)))] - F * n \tag{12}$$

The value of a technology is equal to the probability it is the most innovative times the expected level of innovation given that technology is the most innovative:

(13)

$$v(i,n,s_n(i)) =$$

$$E[X(i,s_n(i))|X(i,s_n(i)) \geq X(j,s_n(j))\forall j \leq n]P[X(i,s_n(i)) \geq X(j,s_n(j))\forall j \leq n]$$

We have mapped the framework for a winner-takes-all market to a discrete version of the framework developed in Section I. Therefore, the results derived in Section I, namely Proposition 2, apply to winner-takes-all markets.

Proposition 5. *In a winner-takes-all setting picking winners can increase social welfare.*

As a concrete example, let each technology be ex-ante equally viable,$v(i,n,s) = v(j,n,s)$, and let $X(i,s)$ take the exponential distribution $F_i(x;s) = 1 - e^{-\frac{x}{s^\lambda}}$. λ determines the concavity of returns to scientific innovation, with a larger λ denoting less concavity (higher returns). This allow for a closed form solution, where $s_n(i) = 1/n$. The expected maximum of n independent and identically distributed exponential random variables with mean $n^{-\lambda}$ is $n^{-\lambda}H_n$, where H_n is the n'th harmonic number.

Let there be $N = 10$ potential innovations and let the fixed cost of developing a new technology be $1/25$. Table 1 displays the social and private value for each level of technology for $\lambda \in \{1/2, 2/5, 1/3\}$.

In all cases the private value to a new entrant is positive, so all technology options are developed in the distributed equilibrium. On the other hand, the socially optimal number of technologies depends on the returns to innovation parameter λ, and in all cases the socially optimal number of technologies to develop is less than that which occurs in the distributed equilibrium.

An important takeaway from this example is that it can be welfare improving

Table 1—Social and private value for winner-takes-all market

n	$\lambda = 1/2$ Social Value	$\lambda = 1/2$ Private Value	$\lambda = 2/5$ Social Value	$\lambda = 2/5$ Private Value	$\lambda = 1/3$ Social Value	$\lambda = 1/3$ Private Value
1	0.960	0.960	0.960	0.960	0.960	0.960
2	**0.981**	0.490	1.057	0.528	1.111	0.555
3	0.938	0.313	**1.061**	0.354	1.151	0.384
4	0.882	0.220	1.037	0.259	**1.152**	0.288
5	0.821	0.164	0.999	0.200	1.135	0.227
6	0.760	0.127	0.956	0.159	1.108	0.185
7	0.700	0.100	0.911	0.130	1.075	0.154
8	0.641	0.080	0.863	0.108	1.039	0.130
9	0.583	0.065	0.815	0.091	1.000	0.111
10	0.526	**0.053**	0.766	**0.077**	0.960	**0.096**

to develop a subset of technologies even though it is unknown which technologies will be ex-post preferred. Using the words of Rosenberg (1998) quoted in the introduction, the "virtue of the marketplace" that "in the face of huge ex-ante uncertainties concerning the uses of new technological capabilities, it encourages exploration along a wide variety of alternative paths" in some cases may turn out to be a vice of the marketplace by encouraging exploration along too many alternative paths with insufficient support to any path explored.

IV. Conclusions

Common wisdom goes that government does not have the knowledge required to pick winners, and therefore should leave such decisions up to the market. I have shown that picking winners can increase social welfare above the decentralized equilibrium. The optimal policy balances the benefits of developing a larger suite of technologies with the benefits of allocating more scarce resources towards each technology developed. The decentralized equilibrium can result in more technologies being developed with less resources devoted to supporting each technology developed than is socially optimal. Technology-specific policies–picking winners–

are most likely to be welfare improving in markets with both innovation in new products and where products are close substitutes so that product redundancy is high.

When decentralized agents have knowledge unavailable to the policymaker, such knowledge should be leveraged to determing which technologies to develop. However, the tendency of the market to develop more products than is optimal is still present. Policy instruments which leverage market information while incentivizing decentralized agents to account for product redundancy may be effective. Additional research may be warranted to determine preferred set of policies to implement.

I have not argued that that technology-specific policies are always welfare improving. Beyond the costs and challenges to implementing such policies, concerns of corruption and rent extraction weigh against any such policy prescription. I have shown that technology-specific policies can improve welfare in some cases, and that the statement that policy should not pick winners is not axiomatic. Markets with high levels of innovation in new products and where products are close substitutes are most likely to see positive improvements from technology-specific policies, though further work needs to be done to determine which specific markets may warrant technology-specific policies, and how such policies may best be implemented.

The policy implications of these results are potentially far reaching. In a wide range of settings from mitigating climate change to developing new vaccines, decision makers must choose how to allocate scarce resources towards innovation. Instead of pursuing an "all of the above" policy, focusing resources towards a smaller subset of options may reduce product overlap and result in better outcomes.

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APPENDIX A Derivation of Planner's Problem

We start with the derivative of the value function as given in equation (4)

$$
\begin{aligned}
V(n) &= \int_0^n v(i, n, s_n^*(i))di - F * n \\
V'(n) &= v(n, n, s_n^*(n)) + \int_0^n v_n(i, n, s_n^*(i)) + v_s(i, n, s_n^*(i)) \frac{\partial s_n^*(i)}{\partial n} di - F
\end{aligned}
\tag{14}
$$

At the optimal distribution of scientists,

$$
v_s(i, \bar{n}, s_{\bar{n}}(i)) = v_s(0, \bar{n}, s_{\bar{n}}(0)) = \lambda_{\bar{n}} \tag{15}
$$

for all $i \leq \bar{n}$. Substituting (15) into (14) and setting n^* to be the point where $V'(n^*) = 0$ gives:

$$
\begin{aligned}
0 &= v(n^*, n^*, s_{n^*}(n^*)) + \int_0^{n^*} v_n(i, n^*, s_{n^*}^*(i)) + \lambda_{n^*} \frac{\partial s_{n^*}^*(i)}{\partial n} di - F \\
v(n^*, n^*, s_{n^*}(n^*)) &= F - \lambda_{n^*} \int_0^{n^*} \frac{\partial s_{n^*}^*(i)}{\partial n} di - \int_0^{n^*} v_n(i, n^*, s_{n^*}^*(i)) di
\end{aligned}
\tag{16}
$$

Finally, note that the new technology developed uses $s_{n^*} n^*$ scientists. Because the total number of scientists is fixed, these must be taken from other technologies.

Therefore $\lambda_{n^*} \int_0^{n^*} \frac{\partial s^*_{n^*}(i)}{\partial n} di = -s_{n^*} n^*$, which gives us:

$$v(n^*, n^*, s_{n^*}(n^*)) = F + \lambda_{n^*} s^*_{n^*}(n^*) - \int_0^{n^*} v_n(i, n^*, s^*_{n^*}(i)) di \tag{17}$$

Which is equation (5).

APPENDIX B Derivation of Competitive Equilibrium

Let w denote the wage rate for scientists. given $\bar{n}$ technologies are in the market, firm i maximizes profits as:

$$\begin{aligned} \pi(i, \bar{n}, s_{\bar{n}}(i)) &= v(i, \bar{n}, s_{\bar{n}}(i)) - F - w s_{\bar{n}}(i) \\ \implies v_s(i, \bar{n}, s_{\bar{n}}(i)) &= w \end{aligned} \tag{18}$$

The market for scientists then determines the wage rate such that:

$$\int_0^{\bar{n}} s_{\bar{n}}(i) di = 1 \tag{19}$$

From equation (18), we have that $v_s(i, \bar{n}, s_{\bar{n}}(i)) = v_s(0, \bar{n}, s_{\bar{n}}(0))$ for all $i \leq \bar{n}$. But this constraint in combination with (19) are the exact same as in the planner's problem. Thus $w = \lambda_{\bar{n}}$ and firms hire scientists to the point of $s^*_{\bar{n}}(i)$, which is the same as in the planner's solution.

Due to the market being competitive, firms will enter whenever they expect to make a profit and will exit whenever they expect to make a loss. Firm profits are decreasing in the number of competitors which means the market equilibrium number of technologies developed is the $\hat{n}$ where profits are zero when the optimal number of scientists are hired. Substituting the optimal number of scientists and the wage rate into the profit function gives:

$$\begin{aligned} &\pi(i,n,s_n^*(i)) = v(i,n,s_n^*(i)) - F - \lambda_n s_n^*(i) \\ \Longrightarrow\ & v(\hat{n},\hat{n},s_{\hat{n}}^*) = F + \lambda_{\hat{n}} s_{\hat{n}}^*(\hat{n}) \end{aligned} \tag{20}$$

Which is equation (6).

APPENDIX C Comparison of Planner Problem and Market Equilibrium With Private Information

Let $\mathcal{A}$ denote gross welfare–welfare without subtracting fixed costs–in the competitive equilibrium:

$$\mathcal{A} \equiv \int_0^m v(\gamma(i), m, \sigma_m(i))di \tag{21}$$

and $\mathcal{B}$ denote gross welfare in the planner's solution:

$$\mathcal{B} \equiv \int_0^n v(\theta(i), n, s_n(i))di \tag{22}$$

Let $\mathcal{C}$ denote gross welfare in the market equilibrium given product redundancy is fixed at the amount in the planner's solution:

$$\mathcal{C} = \int_0^m v(\gamma(i), n, \sigma_m(i))di \tag{23}$$

Finally, let $\mathcal{D}$ denote the gross welfare given private knowledge is utilized but the number of technologies is fixed at the planner's solution:

$$\mathcal{D} = \int_0^n v(\gamma(i), n, \sigma_n(i))di \tag{24}$$

The difference between welfare in the competitive equilibrium and in the planner's solution can be written as follows:

$$\begin{aligned}
&\left[\int_0^m v(\gamma(i), m, \sigma_m(i))di - mF\right] - \left[\int_0^n v(\theta(i), n, s_n(i))di - nF\right] \\
&= [\mathcal{A} - mF] - [\mathcal{B} - nF] \\
&= [\mathcal{A} - mF] + [\mathcal{C} - \mathcal{C}] + [\mathcal{D} - \mathcal{D}] - [\mathcal{B} - nF] \\
&= [\mathcal{D} - \mathcal{B}] + [\mathcal{C} - \mathcal{D} - F(m-n)] - [\mathcal{C} - \mathcal{A}] \\
&= \int_0^n v(\gamma(i), n, \sigma_n(i)) - v(\theta(i), n, s_n(i))di \\
&+ \int_0^m v(\gamma(i), n, \sigma_m(i))di - \int_0^n v(\gamma(i), n, \sigma_n(i)) - F(m-n) \\
&- \int_0^m v(\gamma(i), n, \sigma_m(i)) - v(\gamma(i), m, \sigma_m(i))di
\end{aligned} \tag{25}$$

Which is equation (10)