Incentivizing effort allocation through resource allocation:

Evidence from scientists' response to changes in funding policy

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Abstract

Prior research in management and economics has predominantly focused on how managers or policymakers can shape workers' allocation of effort using output-based or effort-based incentives. In many settings, however, managers may seek to influence workers' effort choices through resource allocation, i.e., changing the cost of securing resources for different projects or activities. In this paper, we develop a formal model to investigate how a worker changes the allocation of a fixed amount of effort across different projects in response to changes in the cost of securing resources for each project. Our model shows how cutting resources available to one project, under certain circumstances, can inadvertently reduce the share of effort allocated to other projects and vice versa. We use the insights from the model to explore the effectiveness of funding strategies designed to influence the research direction of academic scientists. We specifically examine how U.S. scientists working in stem cell research responded to a 2001 policy change that restricted access to federal funding for research in the human embryonic stem cell (hESC) area. In line with our model's predictions, we find that cutting resources for hESC research inadvertently reduced U.S. scientists' output in non-hESC areas of stem cell research–an effect that is strongest among the highest ability scientists. Our findings highlight the complexities of incentivizing effort allocation using resource-based incentives. In particular, we show how altering resource-based incentives in one area can have unforeseen spillover effects on effort allocation in other areas.

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Introduction

There is an extensive literature on how incentive mechanisms change the effort allocation of economic actors.[1] Prior research has predominantly focused on output-based and effort-based incentive mechanisms as complements to market-based and norm-based drivers of agents' behavior (Ouchi, 1979; Lazear, 2018). The output-based incentives reward agents who produce a certain type or level of the desired output. On the other hand, effort-based incentives—also known as behavior-based incentives (Ouchi, 1979)—reward agents for a certain type of behavior or level of effort. In many settings, however, managers seek to influence an agent's effort allocation across different projects or activities by changing the allocation of resources across those projects or activities. Managers, for example, often try to incentivize workers' investment in certain projects by making it easier for employees to access complementary resources (such as capital or equipment) for working on that project. Similarly, policymakers or social movement organizations may try to influence firms' direction of activities by increasing or decreasing the cost of entry into certain domains. Yet, we know surprisingly little about the role and effectiveness of these resource-based incentives in shaping agents' effort allocation and output.[2] Using a formal model and empirically testing its predictions, this paper takes a step to address this gap.

Resource-based incentives are commonly used in contexts where output-based and effort-based incentives have limited practicality. Consider the context of academia where the rewards associated with research are largely reputational and take the form of scientific credit and peer recognition (Stern 2004, Roach and Sauermann 2010, Sauermann and Stephan 2013). Credit is awarded largely by the scientific community based on scientists' assessment of their peers' contribution to scientific

[1] See Lazear (2018), Gibbons (2005) and Gibbons and Roberts (2012) for comprehensive reviews of output-based and effort-based incentive mechanisms.

[2] Note that output-based and effort-based incentives may incorporate a host of work dimensions such as productivity, teamwork, and commitment to the organization. What makes these incentives distinct from resource-based incentives is that the former influences the reward that agents receive from performing a task. Resource-based incentives, in contrast, influence the cost of securing resources required for performing the task.

knowledge (Merton 1957, Dasgupta and David 1994; Stephan 1996). Non-academic actors such as governments and firms, thus, have limited ability to directly influence the allocation of scientific credit in academia. Meanwhile, directly controlling how scientists allocate their effort across different research lines is practically infeasible within the academic context, given the autonomous nature of academic work. As a result, governments and firms have relied heavily on funding and other resource allocation mechanisms as the main lever to influence scientists' research direction and output. In 2016, firms invested approximately $6bn in research performed by academic scientists in the United States alone (National Science Foundation 2018). Similarly, non-profit organizations and governments seek to affect the research direction of academic scientists to areas that are in line with their philanthropic goals or public agenda. Our model highlights some of the counterintuitive implications of using funding and similar resource-based incentives as a device to shape effort allocation.[3]

The model captures the behavior of an agent that has to decide how to allocate a fixed amount of effort among securing resources for and executing two projects A and B. These could also be lines of research, rather than discrete projects, and the model can easily be extended to more than two projects without loss of generality. For each project, the agent first must spend some effort to secure the resources (such as funding, equipment, and material) needed for the project. Once the resources for a project are secured, the agents' production function would be increasing in effort with diminishing returns as they carry out the project. Assuming that agents aim to maximize their output-based rewards, we then calculate how an agent's optimal allocation of effort changes in response to changes in the effort costs associated with securing resources for each project.[4]

The model shows that large enough increases in the effort cost of securing resources for a project can push the agent to allocate their effort entirely to the other project. However, smaller increases in the effort cost of securing resources for a project can lead to an increase in the agent's allocation of effort to that project, at the expense of the other project. It means that, in certain

[3] There is little research on the impact of funding on the research direction of scientists. A notable exception is Myers (2020) which shows that the elasticity of science with respect to funding is very small. Our paper complements Myers' work by providing a theoretical explanation for this low elasticity and further expanding the underlying theoretical mechanisms to non-academic contexts.

[4] Note that the cost of securing resources in our model is equivalent to the amount of effort required to secure those resources.

circumstances, a strategy that hopes to shift the allocation of the agent's efforts from project A to project B by increasing the effort cost of securing resources for project A could inadvertently decrease the share of effort allocated to project B. The model shows that the agent's output in both projects drops as a result. Similarly, the model suggests that reducing the cost of securing resources for a project can, in certain circumstances, reduce the agent's share of effort allocated to that project, while increasing her share of effort allocated to the other project. In other words, a strategy that aims to reduce the agent's effort allocated to project A by reducing the cost of securing resources for project B may instead increase her invested effort in project A. In this case, the agent's output in both projects would increase as a result.

In the context of academic research, our model's predictions imply that cutting funds for a line of research may increase scientists' effort allocated to that line of research at the expense of other lines of research. Such a policy can also stifle scientists' total output. Similarly, increasing funds for a line of research may reduce scientists' effort allocated to that line of research and instead increase their invested effort in other areas. Such a policy can boost scientists' total output across the board.

To test these predictions, we exploit a policy shock in the field of stem cell research in the United States. In 2001, George W. Bush put severe restrictions on federal resources available for human embryonic stem cell (hESC) research based on ethical considerations, rather than its scientific or economic value. We employ a difference-in-differences analysis to estimate the impact of the 2001 policy change on the research behavior of U.S. scientists compared with a similar group of scientists based at institutions in other developed countries that maintained permissive hESC funding policies throughout this period.

In line with our model's predictions, the estimates suggest that the increased effort costs associated with securing resources for hESC research inadvertently reduced (instead of increased) U.S. scientists' research in non-hESC areas of the stem cell domain. The results are consistent with the idea that academic scientists were willing to cut their research efforts in other stem cell areas to invest additional effort in securing alternative sources of funding for their hESC research. We report suggestive evidence that the U.S. scientists changed their institutional affiliations and collaboration patterns to secure new funding sources and equipment for hESC research after the policy change. We

find an increase in the rate at which U.S. scientists had corporate affiliations following the policy change. We also show that U.S. scientists' publications involved more collaborations with industry-affiliated and foreign scientists in the aftermath of the policy change (an effect driven by those previously working at the forefront of stem cell research).

Our model and findings highlight some of the complexities of incentivizing effort allocation via resource-based incentives. In particular, they show how targeting the costs associated with securing resources in one area can have unintended spillover effects on the level of effort that agents allocate to other areas. Accordingly, our results highlight the challenges that policymakers and firms' managers face in managing the direction of research in academia.

2. Theory

2.1 A model of resource-based incentives and allocation of effort

In this section, we develop a simple model of effort allocation by an agent who aims to maximize her output.[5] The agent has a fixed amount of effort and must allocate her effort between two choices. For simplicity, we will use the term "project" to refer to these two choices. However, they can also represent different tasks, lines of work, or any other distinct choices that compete for the agent's share of effort. We use the case of two choices to keep the model simple for expositional purposes.[6]

Agent *i* has a fixed amount of effort to spend on projects and A and B and has to decide how to allocate her effort between the two projects. For each project, the agent first must spend some effort to secure the necessary resources, such as capital and equipment, before producing any output. For the sake of clarity, we call the effort spent on securing resources for either project "resource acquisition effort" and the effort spent on executing either project "productive effort." If agents spend more time securing resources, they will be left with less productive effort for executing projects and, therefore, their overall output drops.

[5] The same model can capture the behavior of agents who want to maximize their utilities. The model is agnostic about the output type.
[6] Note that extending the model to include more than two choices require additional constraints for the model to have a unique closed-form solution.

Once the resources are secured for a project, agents can engage in producing output by investing additional effort in that project. For simplicity, we assume that if agents dedicate the required effort to secure the resources for a project, they will succeed in doing so. All parameters in the model can be considered ex-ante expected values from an agent's point of view.

In the context of academia, for example, scientists may need to raise funding, hire research staff, purchase the necessary equipment, and seek permissions for conducting experiments on human subjects before they engage in a specific research project and accrue scientific credit for it. The amount of effort required to secure resources for a project depends on the availability of resources (including capital, labor, and equipment) as well as the individual characteristics of the agent, such as experience, visibility, network connections, and status.

We assume that the production function $f(e)$ is increasing in effort e (i.e., $\frac{\partial f(e)}{\partial e} > 0$) with diminishing returns (i.e., $\frac{\partial^2 f(e)}{\partial e^2} < 0$). In what follows, we assume that the production function is in the form of $\sqrt{e}$ for any productive effort e invested after the resources are secured. This functional form assumption enables us to provide some numerical examples in the discussion. However, in Section B.1 of the online appendix, we show that the model's predictions hold for any generic function that is increasing in effort with diminishing returns. Note that the two projects are modeled as substitutes, competing with each other for a share of the agent's effort. In the online appendix (Section B.2), we discuss how the results change when the projects are complements. We formally model the agent's production function as follow:

$$f(e_i) = f_A(e_{i,A}) + f_B(e_{i,B})$$

in which

$$f_A(e_{i,A}) = \begin{cases} 0 & if\ e_{i,A} \leq \alpha_i \\ \gamma_{i,A}\sqrt{e_{i,A} - \alpha_i} & if\ e_{i,A} > \alpha_i \end{cases}$$

and, similarly,

$$f_B(e_{i,B}) = \begin{cases} 0 & if\ e_{i,B} \leq \beta_i \\ \gamma_{i,B}\sqrt{e_{i,B} - \beta_i} & if\ e_{i,B} > \beta_i \end{cases}$$

$e_{i,A}$ and $e_{i,B}$ represent the total amount of i's effort invested in projects A and B—i.e., the sum of resource acquisition effort and productive effort invested in each project. α_i and β_i denote the amounts of effort that i would need to incur initially to secure resources for projects A and B. $\gamma_{i,A}$ and $\gamma_{i,B}$ capture how the same unit of invested effort can lead to different levels of output in each project. In the context of academia, $\gamma_{i,A}$ and $\gamma_{i,B}$ can capture the expected scientific impact of each project. They can also incorporate the relationship between the output and utility, enabling us to model the agent as a utility maximizer instead of output maximizer. Formally, $\gamma_{i,A}/\gamma_{i,B}$ represent the ratio of the level of output produced from a unit of effort beyond α_i in project A to the level of output produced from a unit of effort beyond β_i in project B. This ratio (hereafter referred to as γ_i for simplicity) captures the relative attractiveness of investing a unit of effort in project A versus B, if the resources for both have been secured. In the academic context, influencing $\gamma_{i,A}$ and $\gamma_{i,B}$ is often beyond the reach of policymakers or managers. Instead, policies such as allocating more or less funds to certain research projects aim to influence scientists' research direction and output through changing α_i and β_i. Note that the agent's output in each project is driven by her productive effort in that project ($e_{i,A} - \alpha_i$ and $e_{i,B} - \beta_i$) and the productivity multipliers ($\gamma_{i,A}$ and $\gamma_{i,B}$).

Figure 1 shows how the output from each project and the total output changes for varying levels of effort allocation and different sets of parameters. Tab (A) in Figure 1 shows the output levels for a case where both projects require the same level of effort to secure resources ($\alpha_i = \beta_i = 0.2$) and have the same impact ($\gamma_{i,A} = \gamma_{i,B} = 1$).[7] The x-axis is the level of effort invested in project A. Note that the effort invested in project B is simply one minus the amount invested in project A. Given the amount of effort needed to secure resources for either project, the output from project A is zero when the effort invested in the project is anything below 0.2. Similarly, the output from project B is zero when the effort invested in project A is more than 0.8—i.e., the effort invested in project B is less than 0.2. Due to the diminishing returns and the fact that both projects have the same characteristics, the maximum output of 1.1 is achieved when the agent invests the same amount of effort, equal to 0.5, in both.

[7] Prior research suggests that academic life scientists on average spend 40% of their time writing grants and raising funds for their research activities (Scientific American, 2011).

Tab (B) shows a different scenario where both projects require the same level of effort invested by the agent to secure resources ($\alpha_i = \beta_i = 0.2$), but project A is 1.5 times more impactful than project B. ($\gamma_{i,A} = 1.5, \gamma_{i,B} = 1$). In this case, we can see the total output graph is skewed slightly to the right, suggesting that the agent benefits from investing more in project A than in project B. However, the optimal solution would still require investing in both projects due to the diminishing returns to investment. The agent can produce a total output of about 1.4 if they invest approximately 0.6 effort in A and 0.4 effort in B. In contrast, they produce a total output of 1.3 if they invest their effort solely in project A. Moreover, note that the maximum output in this case is more than the maximum output achievable in the previous scenario because project A is 1.5 times more impactful than in the previous case.

Tab (C) shows a more extreme scenario where the return to invested effort in A is twice more impactful than B ($\gamma_{i,A} = 2, \gamma_{i,B} = 1$). In this case, despite the diminishing returns, the agent can achieve maximum output of 1.8 if they invest their effort only in project A. In other words, even at the very high levels of effort invested in project A, the extra output they gain from investing more effort in project A is still greater than the output they gain if they invest that effort in project B.

The same happens if both projects have the same impact, but the effort required to secure resources for project B happens to be much higher than that for project A. Tab (D) shows a scenario where both projects have the same impact ($\gamma_{i,A} = \gamma_{i,B} = 1$), but effort required to secure resources for project B is 0.5 while the effort required to secure resources for A is 0.2. Again, the agent would benefit from allocating their effort solely to project A because securing resources for project B is simply too costly. In this scenario, the maximum possible output is the lowest of all scenarios because project B is too expensive and therefore the agent cannot benefit much from diversifying their efforts even when the extra effort invested in project A is not producing that much extra output.

-- INSERT FIGURE 1 HERE --

Note that α_i, β_i, $\gamma_{i,A}$, and $\gamma_{i,B}$ can vary across individuals. However, we assume that they are exogenous to the choice of individuals' level of effort allocated to projects A and B. Importantly, this assumption means that changes in individuals' level of effort allocated to each project do not influence

the effort cost of securing resources for that project. Therefore, our results below primarily pertain to policies that do not substantially influence the number of individuals invested in each project. They can also capture the short-term response to the larger exogenous changes in α_i and β_i where entry and exit are not instantaneous. In the online appendix (Section B.6), we develop an extended model in which α_i and β_i are both endogenously formed based on the number of individuals working on each project. The results of this model are in line with those reported here.

Given that we are interested in how the agents change the proportional allocation of their efforts between projects A and B, we assume that each agent's total effort ($e_{i,A} + e_{i,B}$) is fixed and normalized to one. Given the exogenously determined values of γ_i, α_i and β_i, each agent chooses $e_{i,A}$ and $e_{i,B}$ to maximize her total output (O_i). Formally, the agent solves the following problem:

$$\underset{wrt\ e_{i,A}, e_{i,B}}{\text{maximize}}\ f_A(e_{i,A}) + f_B(e_{i,B})$$

subject to $0 \leq \alpha_i, \beta_i, e_{i,A}, e_{i,B} < 1;\ 0 < \gamma_{i,A}, \gamma_{i,B};$ and $e_{i,A} + e_{i,B} = 1$

Depending on the values of α_i, β_i, and γ_i, the maximization problem has three possible solutions: the agent invests effort in both projects, just project A, or just project B. The solution that involves the agent investing effort in both projects is:

$$e_{i,A}{}^* = \frac{\gamma_i{}^2(1-\beta_i) + \alpha_i}{\gamma_i{}^2 + 1} \quad if \quad \sqrt{\frac{\alpha_i}{1-(\alpha_i+\beta_i)}} < \gamma_i < \sqrt{\frac{1-(\alpha_i+\beta_i)}{\beta_i}}$$

where $\gamma_i = \frac{\gamma_{i,A}}{\gamma_{i,B}}$. The agent's optimal output in this situation would be:

$$f(e_i{}^*) = \sqrt{(1+\gamma_i{}^2)(1-\alpha_i-\beta_i)} \quad if \quad \sqrt{\frac{\alpha_i}{1-(\alpha_i+\beta_i)}} < \gamma_i < \sqrt{\frac{1-(\alpha_i+\beta_i)}{\beta_i}}$$

Otherwise, the agent will either invest all her efforts in project A if $\gamma_i > \sqrt{\frac{1-\beta_i}{1-\alpha_i}}$ or in project B if $\gamma_i < \sqrt{\frac{1-\beta_i}{1-\alpha_i}}$. The agent will be indifferent between investing her effort in either project if $\gamma_i = \sqrt{\frac{1-\beta_i}{1-\alpha_i}}$. In all cases, $e_{i,B}{}^*$ is equal to $1 - e_{i,A}{}^*$.

The optimal solution provides some intuitive insights. First, as shown in Figure 1b, the agent puts more effort into project A if it is relatively more attractive than project B ($\gamma_i > 0$), and vice versa. Second, the agent invests effort in both projects only if the sum of efforts needed to secure resources

for both are not overwhelming. Intuitively, for the agent to invest effort in each project, the relative attractiveness of that project should outweigh its relative cost. As the effort cost of securing resources for each project goes up, there is more chance that an agent would invest all her effort into the other project, as shown in Figure 1d.

The central question in this paper is how does an agent change her optimal allocation of effort in response to changes in α_i and β_i? A naïve prediction would be that increasing the effort cost of securing resources for one project would push the agent to spend less effort on that project and instead spend more effort on the other. Similarly, a naïve prediction would suggest that decreasing the effort cost of securing resources for one project would increase the relative share of effort invested in that project, all else being equal. For example, a business school dean who wants faculty to spend more time designing new teaching materials may allocate additional funding for writing new case studies. Alternatively, she may impose a penalty in the form of a reduced teaching budget if a faculty member frequently uses old teaching materials. A manager who aims to nudge her employees to invest more effort in long-term projects may allocate additional budget to such projects. Alternatively, she may cut some of the budgets for short-term projects. In all of these cases, the manager or policymaker hopes that reducing the effort cost of securing resources for the more desirable project or increasing the effort cost of securing resources for the less desirable project can push the agents to invest more effort in the former. However, the results from our formal model suggest a more nuanced picture.

We first analyze the response of an agent whose optimal solution involves investing effort in both projects in the absence of any change in the cost of securing resources. There are two potential responses. For a sufficiently large increase in α_i or β_i, the naïve prediction holds—i.e., the agent may shift all of her effort to project B or project A, respectively (see the proof in Section B.3 in the online appendix).[8] Indeed, panel (d) in Figure 1 shows one example of the naïve prediction being correct. A substantial increase in the effort cost of securing resources for project B, from 0.2 to 0.5, pushes the agent to shift all of their effort to project A.

[8] In reality, terminating or abandoning projects may be too costly, which can limit the agent's choices. However, our model does not incorporate any abandonment cost or any shadow of agents' past choices and outcomes.

However, the naïve predictions do not hold for less extreme increases in α_i or β_i. Moreover, decreases in α_i and β_i cannot push the agent to invest only in one project. In other words, if the agent's optimal solution before any decline in α_i and β_i involves investing effort in both projects, the agent would continue to invest effort in both (albeit with a different effort allocation scheme) after the decline in α_i or β_i (see the proof in Section B.5 in the online appendix).

How does the agent's optimal allocation shift if the change in resource acquisition costs does not push her into investing only in one project? We can formally take the derivative of ${e_{i,A}}^*$ with respect to α_i and β_i, respectively, and show that the former is positive, and the latter is negative (see Section B.4 in the online appendix). The results suggest that an increase in the effort cost of securing resources for project A (i.e., α_i) can lead to an increase in the share of the agent's effort invested in project A. Conversely, a decrease in α_i depresses the share of the agent's effort allocated to project A. The predictions are indeed exactly the opposite of the naïve prediction. Additionally, a decrease in the effort cost of securing resources for project B (i.e., β_i) can increase the agent's effort allocated to project A, and vice versa.

To understand these counterintuitive effects, one can consider how the agent allocates her effort after securing the resources. Once the resources are secured, the agent is left with $1-(\alpha_i+\beta_i)$ effort to optimally allocate between the two projects. We can call $1-(\alpha_i+\beta_i)$ the total productive effort. Note that the total product effort is fixed and does not depend on the agent's choice. Once resources are secured, the optimal allocation of the total productive effort depends only on γ_i, i.e., the relative attractivity of project A to project B.[9] In other words, once the resources are secured, the allocation of productive effort between the two projects is independent of α_i and β_i. For example, if α_i increases by 0.1 unit, as long as the agent's optimal solution still requires investing in both projects, the total productive effort reduces by 0.1 unit. However, because the relative attractiveness of investing effort in A versus B remains intact, the ratio of the productive effort invested in A to the productive effort invested in B remains the same (equal to ${\gamma_i}^2$) after the change. Therefore, the 0.1 increase in α_i will

[9] It is easy to show that in the optimal solution, the ratio of the productive effort invested in A to the productive effort invested in B is equal to ${\gamma_i}^2$.

lead to an increase of 0.1 in the effort invested in securing resources for project A and a share of the 0.1 decline in the effort invested in carrying out each project (once the resources have been secured). While the total effort invested in project A increases (equivalent to 0.1 minus the share of the 0.1 reduction in productive effort allocated to carrying out project A), the total effort invested in project B decreases (equivalent to the share of the 0.1 reduction in productive effort allocated to B). Intuitively, we should expect the agent's output in both projects, and hence their total output, will also decline as the result of the increase in α_i.

In the online appendix (Section B.4), we formally show how the output levels change with respect to changes in the effort cost of securing resources. Following the example above, we can conclude that any increase in the effort cost of securing resources for either project can reduce the total productive effort and therefore would reduce the output. In other words, increasing α_i or β_i with the aim of steering agents toward shifting more effort from one project to the other not only can backfire in terms of its effect on effort allocation, but can also reduce the agent's output in both projects and consequently her total output. While reducing α_i or β_i may fail in steering scientists' research direction towards the more desired project, it can nevertheless increase her output.

The results are straightforward for the cases where an agent's optimal effort allocation before changes in resource acquisition costs involves investing effort only in one of the projects. If the agent's optimal effort allocation involves investing effort only in project A or project B, an increase in the effort cost of securing resources for the other project does not change her choice. A large enough decrease in the effort cost of securing resources for the other project may, however, push the agent to invest effort in both projects. Similarly, a decline in the effort cost of securing resources for the only project in which the agent is optimally invested would not change the agent's effort allocation, but will increase the agent's total output. In contrast, a large enough increase in the effort cost of securing resources for the only project in which the agent is optimally invested could persuade the agent to invest effort in both projects (as long as $\alpha_i + \beta_i$ is still below 1).

We can illustrate these effects with a numerical example. Assume that the agent must spend 20 percent of her effort to secure resources for either project and that $\gamma_{i,A}$ and $\gamma_{i,B}$ are both equal to 1. Tabs

(A) to (D) in Figure 2 show how the optimal solution change when the effort cost of securing resources for project A changes. Tab (A) shows the optimal baseline solution when the agent has to spend 0.2 units of effort to secure resources for each project. Both projects are similarly attractive ($\gamma_{i,A} = \gamma_{i,B} = 1$). The optimal solution requires investing 0.5 units of effort in each project to achieve 1.1 units of total output. What happens if there is a sudden decline in the effort cost of securing resources for project A? A 0.1 decline in α_i induces the agent to reduce her invested effort in project A to 0.45 and increase her invested effort in project B to 0.55. Doing so, the agent would still be left with a higher level of productive effort in both projects and can increase its total output to approximately 1.2 (Tab (B) in Figure 2). In contrast, an increase of 0.1 in α_i pushes the agent to increase her effort invested in project A to 0.55; ultimately achieving a lower total output of 1 (Tab (C) in Figure 2). Note that after an increase of 0.1 or a decrease of 0.1 in α_i, the agent's productive effort allocated to project A—i.e., the effort allocated to project A after excluding the effort needed to secure resources for the project—would still be equal to her productive effort allocated to project B. However, if α_i increases substantially from 0.2 to 0.5, the agent would abandon project A and invest her effort exclusively in project B (Tab (D) in Figure 2). In this case, her output drops by to approximately 0.9.

-- INSERT FIGURE 2 HERE --

Tabs (A) and (B) in Figure 3 show how changes in the effort cost of securing resources for project A changes the optimal level of effort allocated to each project and the output from projects A and B, and in total. Both projects have the same level of attractivity equal to 1. For lower values of α_i between 0 and 0.4, any increase in α_i would increase the total effort invested in project A and reduce the total effort invested in project B. While the total amount of effort invested in the two projects change in opposite directions, the amount of productive effort invested in the two projects are the same and gradually declines as α_i increase. Consequently, the level of output from both projects are the same and gradually declines as α_i increased in this range. Total output therefore declines with the same pace. However, once α_i reaches 0.4, it is not optimal for the agent anymore to invest any effort in project A. The effort cost of securing resources for project A is too high. At this point, the agent will allocate their effort entirely to project B. As a result, the output from project A drops to zero and the total output

becomes equal to the output from project B. Naturally, any increase in α_i beyond 0.4 does not change anything as the agent continues to invest all their effort in project B. The level of output remains the same as well.

Tabs (C) and (D) show the same results for a scenario where project A is 1.2 times more attractive than project B. The same dynamics take place. The only difference is that, because now project A is slightly more attractive, the agent continues to invest in it until the effort cost of securing resources for it reaches 0.47. After that, the agent shifts their effort completely to project B.

-- INSERT FIGURE 3 HERE --

2.2 The impact of funding on scientists' research direction and output

We are interested in estimating the causal effect of a change in the effort cost of securing resources for a project on an agent's allocation of effort and output. However, correlational relationships between agents' allocation of effort across projects and the costs associated with securing resources for those projects may be undermined due to reverse causality and omitted variable bias. Consider academia, the empirical context of our paper. The government may increase funding for a line of research in response to scientists' belief that advancements there can lead to breakthrough impact on public health, raising concerns of reverse causality. In such a case, a change in scientists' allocation of effort can drive the governments' funding policy, leading to changes in the effort cost of securing resources for that line of research. Moreover, changes in resource provision and research efforts may both be influenced by common external factors that change the perceived scientific, technological, or economic opportunity in an area of science, leading to the risk of omitted-variable bias.

Therefore, to test our predictions, we need a setting in which the change in the costs associated with securing resources for a project is independent of agents' prior interest and investment in that project. Moreover, the change in costs must affect only a sub-population of agents, leaving a group of unaffected agents from which to construct a counterfactual. Finally, the change in costs should not be predictable far in advance. Predictability could trigger strategic adjustments in agents' allocation of effort prior to the change.

The decision of the George W. Bush administration in 2001 to restrict U.S. federal resources going to human embryonic stem cell (hESC) research provides a setting that meets these criteria. First, the policy shock most likely increased the effort costs associated with securing funding and material for doing hESC research and potentially reduced the effort costs associated with securing funds for non-hESC research in the United States. Our main assumption is that, everything else equal, more federal funding in an area is associated with less effort required to secure funding for research in that area. Second, the decision was driven by ethical and political considerations, rather than by the scientific importance of these research areas or related opportunities. Third, the policy change could not be predicted far in advance. The direction of travel in the U.S. had been toward more permissive policies; Bush's nomination and victory in the 2000 U.S. presidential election were not accurately predictable far in advance. Fourth, the policy should have had a far stronger effect on U.S. scientists working in stem cell research compared with scientists in other countries whose access to domestic public resources was not disrupted.

Our formal model suggests that an increase in effort costs associated with securing funding for hESC research along with a potential decline in effort costs associated with securing funds for non-hESC research[10] can trigger two types of responses. First, assuming that the increase in α_i (the effort costs of securing resources for hESC research) were larger than the decrease in β_i (the effort costs of securing resources for non-hESC research), the model's results suggest that the U.S. scientists would experience a decline in their research output in both hESC and non-hESC areas as the result of the policy.

Second, it may push some scientists who would optimally invest effort in both research areas to suddenly switch all of their effort to non-hESC areas. This could be particularly relevant for junior scholars or those with relatively lower reputations whose effort costs of securing funds for hESC research would likely already have been higher relative to scientists with greater reputations. Additional

[10] The Bush administration has never formally announced a redirection of funds from hESC research to non-hESC areas. The figures suggest that the total amount of federal funding for non-hESC research increased from $300 million in 2001 to $500 million in 2004. Nonetheless, without a counterfactual, we do not know if the increase was proportional to the increase in the level of opportunity in the field or was indeed disproportional. It is possible that the Bush administration might have increased the funding for non-hESC research disproportionally to reduce the level of discontent within the scientific community to some extent.

competition to secure resources for hESC research or the need to be able to signal quality to new partners may mean that the policy change leads them to face a greater increase in the effort costs of securing resources for hESC research relative to scientists with higher reputations. This equates to them facing a de facto greater increase in α_i (the effort costs of securing resources for hESC research) compared to higher reputation scientists.

Additionally, hESC research was an especially high-profile research area that offered higher potential credit-based rewards than other related research areas. In the early 2000s, papers in this sub-field received more than three times higher citations than papers in other areas of stem cell research did. If this credit premium (represented by the difference between $\gamma_{i,A}$ and $\gamma_{i,B}$ in the model) is larger for higher ability scientists, this would give them a greater incentive to pay the effort costs of securing resources for hESC research rather than switching effort to other areas. This would be the case if, for example, high quality hESC research received wider interest from the scientific community than high quality research in other sub-fields, but lower quality research does not receive as proportionally large an increase in attention from the wider scientific community.

Hence an additional increase in the effort cost of securing resources for hESC research could tip lower ability and/or lower reputation scientists towards a situation in which they only invest effort in non-hESC research. Meanwhile, the scientists with greater ability or larger reputations would instead be more likely to invest additional effort in hESC research, directing effort to find alternative sources of money and material for their research, at the expense of lowering the effort allocated to non-hESC areas. Based on these predictions, we test the following three hypotheses in the empirical section of this paper:

Hypothesis 1 (H1): The Bush policy shock in 2001 will have led to a decline in the stem cell research output of the U.S scientists in both hESC and non-hESC domains.

Hypothesis 2 (H2): The Bush policy shock will have led to an increase in the U.S. scientists' efforts in securing alternative sources of funding for hESC research.

Hypothesis 3 (H3): Scientists with higher ability or reputations will have had a relatively larger decline in non-hESC stem cell research output than lower ability/reputation scientists.

Note that we cannot directly observe scientists' allocation of effort in our setting. Our predictions, hence, rely on the assumption that, on average, if a scientist shifts more of her effort to a research area, her relative output in that area increases. However, we believe that our results consistent with these hypotheses provide suggestive evidence in support of our theoretical model. In the next section, we first provide some additional institutional details about our empirical context. We then describe our empirical strategy in more detail and present the results from our analysis.

3. Institutional Details

Stem cells are undifferentiated biological cells that are capable of dividing and differentiating into specialized cell types such as skin cells, nerve cells, or muscle cells. There are two broad types of stem cell: somatic stem cells (which are found in tissues throughout the body) and embryonic stem cells (which can only be derived from the inner cell mass of early-stage embryos). Somatic stem cells can be found in adult or fetal tissue and are already successfully used in treating several health conditions. However, they have had the major limitation of being lineage-restricted, which means that they can only develop into specific forms of cells. Embryonic stem cells were first derived from mouse embryos in 1981 by two independent research teams. A further 17 years passed before James Thomson and his research team at the University of Wisconsin-Madison made the breakthrough of developing a technique to grow and isolate human embryonic stem cells (Thomson et al. 1998). *Science* magazine recognized this advance, and the potential of the stem cell field to generate a vast range of new treatments and therapies, by naming stem cell research its "Breakthrough of the Year" in 1999. Because of their pluripotency and their derivation from human embryos, human embryonic stem cells were viewed by the scientific community as having the highest potential among all types of stem cells to advance current clinical treatments and generate novel therapies (Vogel 1999). Yet, despite their scientific and economic value, there have been ongoing political debates over hESC research driven by concerns about the ethics of research involving cells derived from human embryos.

The first laws prohibiting research on fetuses and embryos in the United States date back to 1973. However, these laws have not been rigorously enforced. In recognition of the enormous opportunities opened up by Thomson et al.'s breakthrough in 1998, the Clinton administration began

to loosen the policies governing federal funds available for embryonic research during its last two years in office. New guidelines were introduced by the National Institutes of Health (NIH) that allowed scientists to use cells derived from spare IVF embryos for research purposes. This was seen by the scientific community as a strong statement of support for hESC research from the federal government (Gottweis 2010).

However, in mid-April 2001, President Bush suspended applications before the first grants could be made. Subsequently, the administration announced its new stem cell policy on August 9, 2001. Despite the scientific community's optimism about the trend toward increased federal funds being made available for hESC research, the policy banned any federal funding for research on new hESC lines. Limited federal funding was permitted for research on pre-existing hESC lines developed before 2001. A lack of genetic diversity and contamination of the 21 pre-existing hESC lines also limited their scientific value. At the same time, federal funding was increased for non-human embryonic stem cell research. During Bush's first term as president, NIH invested an average of $15 million per year in hESC research, while non-hESC stem cell research investments grew from approximately $300 million in 2001 to over $500 million in 2004 (Johnson and Williams, 2007).

The Bush policy also created a significant organizational burden for U.S. scientists managing labs that also received industry, non-profit, or state government funds for hESC research. Many of these research labs received federal funding from NIH for other projects. The Bush era regulations meant that NIH funds could not be used for non-approved hESC research. This extended beyond immediate materials to the laboratory's equipment, student scholarships, and other overhead items that would typically have been managed at the laboratory level. As a result, U.S. scientists had to strictly delimit the use of equipment between hESC and non-hESC research. Over time, some non-federal actors—such as state governments and foundations—began offering resources to U.S.-based scientists for hESC research. Overall, the Bush policy increased the effort costs associated with securing funding and research material for hESC research relative to those faced by scientists in other countries. The Bush administration's restrictions on hESC research were lifted in 2009 following the election of President Obama.

The Bush administration's stem cell policy set off waves of concern in the scientific and regulatory communities that the United States would fall behind in an important area of science (Fletcher 2001, Holland et al. 2001, Vogel 2001, Holm 2002, Holden 2004, Johnson and Williams 2007). In the wake of these concerns, several studies have sought to document the impact of the Bush policy on subsequent hESC research in the United States relative to other countries (Levine 2004, Owen-Smith and McCormick 2006, Scott et al. 2009, Furman et al. 2012, Vakili et al. 2015). Using five less controversial biomedical research areas as a baseline, Levine (2004) reports that the share of hESC publications credited to U.S. scientists dropped in 2003 and remained at this lower level in 2004. Studying the same period, Owen-Smith and McCormick (2006) also report a decline in the relative share of hESC publications by U.S. scientists compared with scientists elsewhere in the world. Looking at an extended timespan, Vakili et al. (2015) find that the U.S. share of hESC publications stopped declining after 2003, increased slightly in 2004, and then remained consistent at about 33 percent of total hESC publications until 2010. Furman et al. (2012) similarly find that the United States' relative production of hESC research decreased between 2001 and 2003 but rebounded in the subsequent years.

While these studies report a decline in the share of global hESC science output produced by U.S. scientists, it is not clear whether this reflects changes in the research direction of U.S. scientists, a decline in the output of U.S. scientists, or an increase in the number of stem cell scientists in other regions of the world. These studies provide important insight into the impact of the Bush policy on the total share of hESC research carried out by scientists in the U.S. However, the country-level analyses do not show how the funding regime change affected individual scientists' research direction. In this study, we focus on the intensive margin of the change in the funding regime—that is, the impact of the policy on the incumbent scientists' research direction and behavior. The policy could plausibly also influence the research behavior and direction of new scientists entering the field. The total effect of the policy would then be the net effect of the changes on both the intensive and extensive margins.

4. Empirical Design

4.1 Data

We examine the effects of changes in scientific funding on scientists' research direction, output, collaborations, and affiliations using the drastic change in federal funding for hESC research introduced by the Bush administration in the United States in 2001. We begin by using the Scopus database to identify all scientists who had a publication in a stem cell field before 2001. First, to identify the stem cell publications, we search for articles that mention "stem cell" or its variants in their titles, abstracts, or keywords. We then identify scientists who were affiliated only with U.S.-based organizations in the five years before the Bush policy announcement, according to their affiliations listed on publications. Using this approach, we create a sample of all U.S. scientists who had published at least one article in a stem cell field in the five years from 1996 to 2000. We consider these scientists to be active in the stem cell field and thus potentially affected by the policy change.

We then use parallel criteria to identify all scientists who had a publication in a stem cell field and were affiliated only with organizations in one of several countries that had more flexible funding/policy regimes compared to the Bush policy—both during the years prior to 2001 and that continued to have less restrictive policies throughout the sample period. Many countries lacked specific policies or regulations that were applicable to hESC research before the isolation of hESCs in 1998. We limit the control scientists to other countries that were classified as developed countries by the World Bank for the full sample period. This is to mitigate the risk that our results could be biased by countries with more rapid economic development also having larger increases in public funding for science. The final set of control countries is Australia, Belgium, Canada, Denmark, Finland, Greece, the Netherlands, New Zealand, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. The scientists based in the U.S. form the treatment group, and the non-U.S.-based scientists form the control group.

For each scientist in our sample, we extract the author information, affiliations, abstracts, and citation figures of all papers she authored until 2012. We exclude those scientists whose first publication appeared before 1976 (25 years before the policy change) to mitigate the risk that a reduction in publication rates after the 2001 policy change could be driven by older scientists retiring from active

research. The above procedure yields 7,710 scientists, more than 300,000 scientist-publication observations, and 170,000 scientist-year observations. During the 1997–2012 period, which is the focus of our empirical analysis, we have approximately 220,000 scientist-publication observations and 120,000 scientist-year observations. In the five years before the Bush policy was introduced in 2001, 70 percent of the scientists were exclusively U.S.-based, and 30 percent were based exclusively in one of the control countries.

To categorize the full set of publications into various sub-fields of stem cell research, we performed an initial keyword search to create an inclusive set of articles that provided any indication of embryonic research. Next, graduate students in biology from two leading universities in the field manually coded articles as belonging to hESC or to other non-hESC sub-fields of stem cell research. All research assistants had completed at least one year of graduate coursework in cell biology. All papers in the set of articles were read by at least two research assistants. The research assistants made the same categorization decision on more than 90 percent of articles. In cases of disagreement, all potential hESC articles were coded by a third research assistant.

4.2 Dependent Variables

Our interest in this paper is to understand how the shift in funding resources influenced scientists' research direction and output. Our first set of dependent variables measure scientists' research direction and output using their citation-weighted number of publications per year across different sub-fields of stem cell domain (whether in hESC and non-hESC research). More specifically, we use the natural logarithm of 1 plus the number of forward citations to scientist *i*'s publications in year *t* in hESC research, non-hESC stem cell research, and at the aggregate level. The hESC sub-field represented the highest impact of stem cell research at the time of the Bush policy change, followed by non-human animal embryonic stem cell research. Papers in our sample published in the hESC sub-field from 2001 to 2003 had an average of just over 300 citations. Papers in the animal embryonic stem cell sub-field received an average of approximately 100 citations with non-embryonic stem cell papers receiving about 70 citations on average. The median paper in each of the three sub-fields received approximately 250, 40, and 30 citations, respectively. This shows that during the period in which the Bush policy

change took place, hESC research represented the most impactful area of the stem cell field by a large margin and offered scientists the greatest opportunities for reputational rewards.

We use citation-weighted publications because this captures the extent to which a scientist's allocation of research effort to a given area generates scientific impact (as the scientists' outcome of interest). Research effort affects both the quantity and quality margins of scientists' output. Using raw publications as the main dependent variable would miss the extent to which changes in U.S. scientists' research efforts are reflected in both the quality and quantity of research output (relative to control scientists with a prior output of similar impact). By focusing on citation-weighted publications we ensure that we measure how far the research inputs of scientists' human capital, effort, and research resources are generating their intended output of scientific impact. In the online appendix, we show that the results are robust to using the simple count of publications.

Our second set of dependent variables allow us to examine whether scientists respond to the policy change by acquiring new affiliations or initiating new collaborations. Following our model's prediction, we expect scientists to spend additional time looking for new sources of funding for their hESC research. We use the author affiliation information from each publication on Scopus to identify the institutional affiliations of both the focal scientist *i* and each of *i*'s coauthors on a given paper. The affiliations data allow us to examine whether a focal scientist acquires a new type of institutional affiliation. We identify whether an institution with which a scientist is affiliated belongs to one of two categories: academic research, hospitals, and other health service provision; or corporations. We group academic and health service institutions together because it is very difficult to determine whether a scientist should be categorized as affiliated with a hospital or a university from their affiliation data. This distinction is blurred for many institutions with large numbers of observed authors and publications (e.g., "University Hospitals" or "Academic Medical Centers"). We create two dummy variables that indicate whether scientist *i* was affiliated with an institution in each respective category in year *t*. Where a scientist does not have an identifiable affiliation because we do not observe a publication in a given year, we interpolate *i*'s affiliation between observed data points by finding the most proximate observed affiliation. Where there is an even number of years between observed affiliations, we break ties by attributing the subsequent affiliation to the scientist.

We also use the affiliation information on a publication to identify the country in which each of *i*'s coauthors' institutions were located. We create a set of dummy variables to indicate whether scientist *i*'s publications in year *t* involve coauthors from a set of countries with more permissive funding/policy regimes on papers in stem cell sub-fields. We repeat this procedure to create a similar set of dummy variables for the country to indicate whether scientist *i*'s publications in year *t* involve industry-affiliated coauthors on papers in stem cell sub-fields.

4.3 Independent Variables

Our first independent variable is an indicator variable intended to capture whether a scientist was with based at a U.S. institution immediately prior to the Bush policy change in 2001, and hence was directly affected by the shock. More specifically, we create a time-invariant dummy variable equal to 1 for all scientists whose primary affiliations were exclusively with U.S.-based institutions during the pre-shock period, and equal to 0 for all other scientists in our sample.

We also create indicator variables to distinguish each of the following periods: 1997–2001, 2002–2005, 2006–2009, and 2010–2012 (when our dataset ends). The 1997–2001 indicator variable is used as the base and captures the period before the policy change. The other three indicators capture post-shock periods. The interaction of these indicators with the indicator for the U.S.-based scientists (during the five years prior to 2001) enables us to capture the short- and long-term effects of the Bush policy on U.S. scientists in the years following the 2001 policy change. Since we include scientist fixed effects in all empirical specifications, we do not include separate independent variables for scientists' country of affiliation. Similarly, because of the inclusions of year fixed effects, we do not need to include additional indicators for these time windows in our analysis. We also use the variance in the level of scientists' investment in stem cell research areas before the policy shock for robustness checks. To test Hypothesis 3, we exploit heterogeneity in scientists' pre-2001 publication records to examine whether the effects are most pronounced among scientists with higher ability or reputation.

4.4 Identification Strategy

To identify scientists' responses to the change in policy regime, we employ a difference-in-differences analysis. We compare the change in the U.S. scientists' research outcome and behavior after the policy change in 2001 with those of their counterparts in countries with flexible policies toward hESC research. Since the population of U.S.-based scientists may have systematically different characteristics from our control group of scientists, we use coarsened exact matching to create a matched sample of U.S. and control scientists (Blackwell et al. 2009, Iacus et al. 2011). We match on total citations to all publications and citations to stem cell papers for each of the four years prior to the policy regime change in 2001. In matching scientists, we also include the year in which they first published and the year of their first stem cell publication, whether they had an (animal or human) embryonic stem cell publication in the five years before 2001, and whether they had been affiliated with industry or academic institutions at any point during that period. Matching on these variables is intended to ensure that scientists of similar research trajectories in stem cell research are being compared in the analysis.

This procedure results in 4,605 scientists in the matched sample, of whom 4,360 were affiliated exclusively with academic institutions or health centers prior to the policy change in 2001. Approximately 60 percent of matched scientists are based in the U.S. during the 1996–2000 period, and 40 percent in the control countries. We weight each set of matched scientists following the guidance in Blackwell et al. (2009). This means that where multiple treatments and/or control authors are assigned to a specific covariate-balanced stratum, we do not lose information from the additional units that would be discarded in one-to-one matching. We report our core results for both the whole sample and the matched sample.

Our sample provides panel data on scientists' output, institutional affiliations, and coauthoring patterns from 1997 to 2012. We use the following specification for our core analysis:

$$Y_{it} = \beta_0 + \beta_1 . US\_scientist_i . T0205_t + \beta_2 . US\_scientist_i . T0609_t + \beta_3 . US\_scientist_i . T1012_t + \tau_t + \delta_i + \varepsilon_{it}$$

where Y_{it} denotes the dependent variable of interest in each regression for scientist i in year t. $US\_scientist_i$ is a dummy variable equal to 1 if scientist i was affiliated exclusively with institutions

in the United States during the pre-shock period (and 0 otherwise), and $T0205_t$, $T0609_t$, and $T1012_t$ are dummy variables respectively equal to 1 for observations during each of the respective periods after the policy change, namely 2002–2005, 2006–2009, and 2010–2012 (and 0 otherwise). The main coefficients of interest are β_1, β_2, and β_3, which respectively capture the differential effects of the Bush policy on U.S. scientists during each of the post-shock periods. In regressions for which the dependent variable is citation-weighted hESC publications, we restrict our sample to the 1998–2012 period. This is because the breakthrough research by Thomson et al., which opened up the major new opportunities for further hESC research and hence changed the opportunities and incentives for scientists to work in this field, was published in 1998. We also repeated our empirical analysis using shorter, three-year windows; the results are similar in each case. It is important to note that scientists compete with each other globally for discovering and publishing new findings, therefore a perceived change in the relative rewards to doing hESC research would affect both U.S. and non-U.S. scientists similarly.

Year fixed effects are captured by τ_t, and time-invariant individual characteristics are controlled for using scientist fixed effects, δ_i. Therefore, our regressions identify the within-scientist change in scientists' output, collaboration patterns, and affiliations following the change in policy regime for U.S. scientists compared with non-U.S. controls. Table 1 summarizes the definitions of the variables used in the analysis.

-- INSERT TABLE 1 HERE --

5. Results

5.1 Summary Statistics

The summary statistics presented in Table 2 show that scientists in our sample have on average 83 citation-weighted publications per year during the period from 1997 to 2012 inclusive, of which approximately one-sixth involve stem cell research. The scientists have an average of approximately 14 stem cell publications with half a citation-weighted publication in the hESC sub-field per year. In our empirical analysis, we exclude all scientists with industry affiliations at the time of the policy shock unless otherwise noted. These scientists would have been less reliant on public funds for research resources and therefore would have faced less of a direct incentive to switch research areas due to

changes in the accessibility of public funds. In the full sample, 11 percent of scientists had an industry affiliation at the time of the policy change. The statistics for the matched sample follow a similar pattern in terms of the distribution of publications across research areas, although the publication rates are attenuated because of the lack of proximate matches available for scientists with extremely high research outputs. Scientists in the matched sample also had fewer industry affiliations and a higher propensity to be affiliated with a university or health center.

-- INSERT TABLE 2 HERE --

Table 3 compares the characteristics of U.S. and non-U.S. scientists in the full sample and the matched sample (adjusting for the matching weights) during the five years prior to the policy change in 2001. The t-test statistics for the full sample show that U.S. scientists produced on average more citation-weighted publications, overall and in most stem cell fields, in the pre-shock period. Their first publications are also a few months earlier than those of their non-U.S. counterparts. Their affiliation profile differs significantly, with more control scientists having academic affiliations and fewer having industry affiliations. On average, U.S. scientists have higher output in terms of citation-weighted publications per year. The t-test statistics for the matched sample show no significant difference between the matched U.S. and control scientists on any of the output or affiliation variables before the shock.

-- INSERT TABLE 3 HERE --

5.2 Changes in Scientists' Research Direction

We now turn to examining how the policy change led to changes in U.S. scientists' research relative to those in control countries. Table 4 presents our first set of results. This table shows the relative change in the citation-weighted research output of U.S. scientists following the change in policy regime in the United States. We report our main results for both the full and the matched samples to ensure that our interpretation of the findings is not driven by a selection effect from including only U.S. scientists for whom there are controls meeting the matching criteria. Panel A presents the treatment effects for the full sample. In Panel B we move to analyze the matched sample to understand the relative effect of the Bush policy on U.S. scientists relative to scientists who were more similar to them prior to the policy

shock. The dependent variable in Model 1 is scientists' citation-weighted publications across all fields. In Models 2 and 3, the dependent variables distinguish between scientists' stem cell and non-stem cell research output. This is further broken down to hESC and non-hESC sub-fields of stem cell research in Models 4 and 5 to capture the change in the research direction of U.S. scientists within the stem cell field compared to the control scientists.

Model 1 of Panel A shows that there is a significant decrease in U.S. scientists' total research output in the unmatched sample following the change in policy regime. The point estimates suggest that U.S. scientists produced 12 percent fewer citation-weighted publications than scientists in control countries in the four years following the funding policy change. This gap increases over the subsequent periods. Results from the matched sample in Panel B do not show an immediate significant decrease in U.S. scientists' overall research output relative to their matched controls. One reason for the difference between the estimates in the full and matched samples may be the under-representation in the matched sample of the scientists who had the very highest citation rates in the pre-shock period. In additional analysis (available from the authors), we find some evidence that those with the very highest citation rates in the pre-shock period had the greatest drops in overall citation-weighted output in later years (among both U.S. and control scientists).

-- INSERT TABLE 4 HERE --

Focusing only on stem cell research, we find in Model 2 that the relative citation-weighted stem cell publications of U.S. scientists decreased significantly in both the unmatched and the matched samples following the federal policy change in 2001. The point estimates in the unmatched sample suggest that U.S. scientists experienced approximately a 12 percent decline in their citation-weighted stem cell publications following the shock. The estimates from the matched sample report a slightly more moderate effect, but again it is significant in each period. Our point estimates suggest that there was an initial decline of approximately 10 percent in the citation-weighted stem cell publications of the U.S. scientists compared with their matched counterparts. This gap appears to reduce over time, but a 4 percent difference endures in the 2010–2012 period. Overall, the results in Model 2 indicate that the change in funding regime had a lasting negative effect on the U.S. scientists' total output within the stem cell domain.

We do not hypothesize about the effect of the Bush policy on non-stem cell research in this paper (since to do so would require more detailed information about the relative attractiveness of different non-stem cell research areas). However, one concern is that—instead of being driven by our hypothesized mechanism—the results on U.S. scientists' stem cell research output could simply reflect a relative decline in U.S. public funding for science compared to control countries during this period. If this were the causal mechanism, we should expect to see a similarly sized negative effect on U.S. scientists' non-stem cell research output. However, our results indicate that there is no significant change in their non-stem cell output relative to the matched controls.

Moving to a more fine-grained analysis, Models 4 and 5 report the change in the citation-weighted output of U.S. scientists for non-hESC and hESC sub-fields of stem cell research, respectively. The results in Model 4 show a clear, sustained post-shock decline in U.S. scientists' stem cell publications outside the hESC research sub-field. Among the matched sample of scientists, the magnitude of this effect decreases over time and is only marginally significant by the final time period. These decreases in U.S. scientists' non-hESC stem cell publications occur despite the fact that the new policy reduced the availability of resources for hESC research and potentially increased the amount of federal resources available for research in other sub-fields of stem cell research. These findings are consistent with Hypothesis 1. The estimates from Model 5 do not provide clear evidence of an effect on the U.S. scientists' citation-weighted publications in the hESC domain in either the unmatched or the matched samples following the change in policy regime. Although there is a decrease in U.S. scientists' citation-weighted hESC publications, the estimates are not significant. Therefore, we cannot make any strong conclusion about the impact of the policy on the U.S. scientists' hESC research output. However, the nonsignificant effects for the hESC domain may be due to the less frequent and hence more noisy publication trends in that area, particularly in the pre-period.

Figure 4 shows U.S. scientists' non-hESC stem cell research output relative to that of the untreated scientists from control countries before and after the Bush policy was introduced. There is a clear decline in citation-weighted non-hESC stem cell research output in both the full (Panel A) and matched (Panel B) samples. There is little evidence of a negative pre-trend for either area of stem cell research. We create similar graphical representations of our results for hESC research, which are shown

in Figure 5. In the full sample, there appears to be a significant decrease in U.S. scientists' hESC research output in the immediate post-shock period, in line with Hypothesis 1, which ameliorates over time. In the matched sample, while the coefficients are consistently negative, the effects are not significant. Figure A.1 shows the equivalent trends for U.S. scientists' relative non-stem cell research.

--INSERT FIGURES 4 & 5 HERE--

Hypothesis 3 also suggests that the effect would be largely concentrated among scientists with greater ability or larger reputations. To test this in our setting, we split the sample according to scientists' citations in the five years prior to the policy shock relative to their cohort of scientists whose first publication is observed in the same year. These higher-quality scientists should, on average, have lower effort cost of securing resources if these become more competitive and have greater ability to have higher impact publications in the hESC sub-field.

The results in Table 5 show that it is the higher ability scientists who have the strongest response to the Bush policy change. There is little evidence of any change in the citation-weighted publication rates of the lower ability U.S. scientists relative to their matched controls in stem cell research. However, there is an immediate significant decline of approximately 16 percent in the non-hESC stem cell research output of the higher-ability U.S. scientists. The results are consistent with Hypothesis 3. They demonstrate the important risk of adverse selection, highlighted in the model, where funders seek to use the effort cost of securing resources as incentive mechanism to attract scientists to research areas.. Namely, where funders provide more resources to one area that offers fewer reputational rewards, those who are most capable of achieving those rewards will often be those whose ability and reputation makes them most willing and able to resist the intended incentives.

-- INSERT TABLE 5 HERE --

We carry out a series of robustness checks designed to ensure our results are not driven by any other changes in policy that may have occurred at a similar time to the stem cell funding shock. In Table A.1 in the online appendix, we show that the results are larger and more persistent for U.S. scientists who had a greater share of their pre-shock research output in the stem cell area. Scientists with relatively low levels of output in the stem cell area before 2001 were less likely to be affected by the Bush hESC policy. They had relatively more projects in other fields and so the marginal changes in stem cell

research funding should have had a smaller effect on their overall output. These scientists were typically more specialized in other nearby areas, such as gene therapy or tissue engineering. The split-sample results also suggest that any general changes in NIH funding levels during the Bush administration are unlikely to be driving our results. There is no clear reason why the negative effects on research output due to changes in overall funding levels for academic science would more strongly affect U.S. scientists with greater attachment to the stem cell field. In Table A.2, we recreate our results using raw publication numbers in each scientific domain as the dependent variable (rather than citation-weighted publications). The results show a clear decline in U.S. scientists' number of stem cell publications relative to their matched controls after the policy shock driven by changes in the relative rate of non-hESC publications. Moreover, in Table A.3, we show that the decline in the non-hESC research was largely driven by a decline in lower-quality papers. This is consistent with our model's prediction that under diminishing marginal returns to efforts, scientists are more likely to forgo marginal projects in the non-hESC area in order to secure resources in the hESC area.

As a further robustness check to ensure the effects are driven by the policy change, we examine the effects of the policy on U.S. scientists who had an industry affiliation in the five years prior to the shock. These scientists were not as exposed to federal funding for securing research resources. Therefore, if the Bush policy is driving our core results, we would not expect these scientists to exhibit a different publication pattern from their matched controls after the policy shock. The results of this analysis are presented in Table A.4 of the online appendix. They show that there are no significant differences between U.S. scientists' and control scientists' post-shock publication output in either the hESC or other stem cell sub-fields among scientists with pre-shock industry affiliations. Additional robustness checks (available from the authors) include incorporating country-specific linear time trends and one-by-one exclusion of control group scientists by country.

Overall, it appears that U.S. scientists experienced a significant decline in their non-hESC stem cell research output when the new funding regime was introduced. Our results are consistent with U.S. scientists shifting some of their research efforts in non-hESC sub-fields toward securing resources needed to support their research in the hESC domain.

5.3 Scientists' Strategic Behavior – Institutional Affiliations

To provide more evidence on whether U.S. scientists sought alternative sources of funding for hESC research after the policy shock, we examine how the policy change affected U.S. scientists' institutional affiliations and collaboration patterns. Prior research has shown that one reason some scientists choose industry employment over academia is easier access to financial and material research resources (Owen-Smith and Powell 2001, Roach and Sauermann 2010). Similarly, we know that access to resources is an important motivating factor for academic scientists choosing to collaborate with industry on projects (D'Este and Perkmann 2011, Tartari and Breschi 2012). Additionally, as science becomes more global and communication technologies facilitate more detailed interactions at a distance, international collaborations between academic scientists have become more common (Adams 2013, Wagner et al. 2015). In our setting, U.S. scientists may seek to collaborate with scientists in other countries that have more permissive funding regimes to access research resources.

Table 6 shows how U.S. scientists' propensity to acquire industry affiliations was affected by the policy change. For this analysis, we include all authors regardless of prior affiliations and do not exclude those with industry affiliations at the time of the policy change (as in the citation analysis). This allows our model to estimate changes relative to the prior switching rate in earlier years, rather than have this artificially set to zero by excluding scientists with an industry affiliation in the pre-shock period. The results in Model 1 indicate there was a general trend toward industry employment for U.S. scientists relative to their matched controls. To understand what is driving this trend, in Models 2 and 3 we split the sample according to whether scientists had very high investment in stem cell research areas (for whom two-thirds of their citations received to papers published in the five years before the policy change were to stem cell research). Here, we find clear evidence that the increase in the rate of industry employment among U.S. scientists relative to those in control countries is driven by scientists more heavily invested in stem cell research.

-- INSERT TABLE 6 HERE --

In Model 4 we exclude all scientists with only one publication prior to the policy change to ensure that the results are not driven by a specific subset of early-career scientists, or those less engaged in academic publishing, who may have different incentives in the labor market from the general

population of scientists. In fact, the results appear to be strongest among the more established scientists with larger publication records. Models 3 and 4 show that U.S. scientists who were most heavily specialized in stem cell research had a significantly increased rate of acquiring industry affiliations after the policy change. Interpreting this coefficient relative to U.S. scientists' baseline rate of having industry affiliations in the year of the policy change, our results suggest that a U.S. scientist was approximately 15 percent more likely to acquire an industry affiliation after the policy change. Notably, the largest relative increase is in the immediate aftermath of the policy change, suggesting that this was a driver of the labor market decisions.

Models 5 through 8 show the changes in the relative propensity for U.S. scientists to hold a university or hospital affiliation. Although there is no clear trend in the entire matched sample, Models 7 and 8 show that when we limit the analysis to those who were heavily invested in stem cell research, we find a clear and immediate decline in the propensity of U.S. scientists to hold university or hospital affiliations. We can also see that the percentage-point increase in industry affiliations among U.S. scientists heavily invested in stem cell research is very similar to the percentage-point decrease in academic affiliations. This suggests that the U.S. scientists are transitioning to industry from academic employment rather than just acquiring additional affiliations as a resource acquisition strategy. To ensure that the results are not driven by the matching process, we repeated the analysis in Table 6 using the full sample of scientists. The results (available from the authors) follow a very similar pattern to those in the matched sample. Figure 6 shows the changes in U.S. scientists pre- and post-shock affiliations graphically based on the specifications in Models 4 and 8 of Table 6.

--INSERT FIGURE 6 HERE--

We also examined the research output of scientists who made the transition from academia to industry following the policy shock. The results of this analysis are reported in Table A.5. We find that U.S. scientists who acquired industry affiliations after the policy change had greater hESC citation-weighted research output on average in the four years immediately following the policy change relative to U.S. scientists in academia. We also find that U.S. scientists with industry affiliations had higher hESC output relative to control country scientists working in industry. This suggests that there may have been selection of U.S. scientists who wanted to do hESC research into industry employment

following the policy change. We do not observe similar effects for U.S. scientists in other research areas during this period nor other time periods.

5.4 Scientists' Strategic Behavior – Collaboration

An alternative mechanism for scientists to secure research resources is to collaborate with scientists at other institutions with greater access to such resources. In our setting, U.S. scientists whose access to resources was restricted by the policy change may have used collaborations with industry or foreign scientists whose resource access was unaffected to work on hESC research projects. We examine the publications of U.S. scientists to see whether their propensity to involve coauthors from either industry or countries with flexible policy regimes increased after the policy change. Table 7 shows changes in the rate at which U.S. scientists' publications across different research areas were coauthored with scientists from industry and foreign countries with flexible regimes. We use time-period fixed effects in the models in Table 7, rather than the year fixed effects used in the rest of the analysis. This is because some types of collaboration for certain sub-fields of stem cell research were relatively rare in a given year during the sub-field's nascent phases. For brevity, we present the results for collaborations in hESC research, non-hESC stem cell research, and for across all fields of research.[11]

-- INSERT TABLE 7 HERE --

The results in Model 1 show that, following the policy change, U.S. scientists' publications were significantly more likely to involve hESC research conducted in collaboration with industry scientists than match controls in countries with permissive funding regimes. However, this effect declines over time, concomitant with increases in domestically available resources for hESC research. By comparison, Model 2 shows that U.S. scientists' publications in the initial post-shock period were significantly less likely than the matched controls to involve collaboration with industry scientists on research in non-hESC sub-fields of stem cell research. Model 3 also shows a significant decrease in the

[11] The results are attenuated and often unclear in the full sample. In the unmatched sample, the distributions of scientists vary significantly in their past citation-weighted research output and areas of focus. Scientists with very different past productivity (and consequently reputation) and research focus will have different incentives and opportunities to form new collaborative relationships. Therefore, we believe that for this analysis, in particular, the matched sample provides a more accurate reflection of how scientists respond strategically to changes in resource incentives by initiating new collaborations.

probability that a U.S. scientists' publication in any field involves collaboration with industry relative to the control scientists. It appears that U.S. scientists' publications were more likely to involve collaborations with industry scientists in the hESC sub-field after the policy change compared with collaborations in other research areas. We take this as suggestive evidence that some U.S. scientists acted strategically to be able to conduct research in the more impactful hESC sub-field, which offered greater potential reputational rewards.

We now move to analyzing U.S. scientists' collaborations with scientists in foreign countries who had access to public resources. Model 4 shows that there was no significant difference in the rate of collaboration on hESC research with such scientists on U.S. scientists' publications compared with their matched controls. However, after the U.S. federal funding restrictions were relaxed, we see that U.S. scientists' publications were significantly less likely to involve collaborations on hESC research with foreign scientists in flexible funding regimes relative to the control scientists (unlike other sub-fields). Notably, Models 5 and 6 show that, while there was no change in the rate of U.S. scientists' publications having hESC research collaboration in the 2002–2005 period, there was a decline in the propensity for U.S. scientists' publications to involve collaborations on non-hESC stem cell research or any collaborative research with foreign scientists in countries with more flexible hESC policies.

Taking non-hESC areas of stem cell research as a counterfactual, the results in Table 7 show that, compared with publications by similar scientists in unaffected countries, U.S. scientists' publications were more likely to involve collaborations with foreign scientists in the hESC sub-field after the policy change relative to collaborations in other research areas. In Table A.6 we show that these results do not appear to be driven by policy changes that supported greater cross-border collaboration in European science during this period. The results show that, during the Bush era, there is an increase in the rate at which U.S. scientists' publications involve collaboration on hESC research with scientists from countries with flexible policy regimes compared to non-European control scientists.

In Table A.7 of the online appendix, we provide further evidence that the changes in collaboration patterns in the immediate post-Bush policy period are driven by scientists' strategic behavior to secure resources for hESC research. We show that the main effects in Table 7 are driven by those U.S. scientists who had publications in embryonic stem cell research before the policy shock.

These scientists were working at the forefront of stem cell research and thus both had the incentives to keep working at the research frontier and were likely most attractive to potential collaborators with resources.[12] Overall, our results show changes in U.S. scientists' affiliations and collaboration patterns that are consistent with Hypothesis 2.

The collaboration and affiliation results provide additional evidence that our core results are not simply driven by U.S. scientists exiting the stem cell research area. For example, if scientists were frustrated with the politicization of funding for hESC research, which was at the forefront of the field, this may lead them to have switched their research direction out of stem cell research. However, the results in this section imply that many U.S. scientists acted strategically to secure resources for hESC research. Moreover, our core results also show that there was no increase in U.S. scientists' citation-weighted or raw publication counts in non-stem cell domains. If the U.S. scientists were simply exiting stem cell research, we would expect to see an (at least, partially) offsetting increase in their non-stem cell research output. Similarly, Table A.1 shows that U.S. scientists with a greater share of their prior research output in the stem cell field relative to other research areas, have lower rates of non-stem cell research output in the longer term (compared to their matched controls). This effect appears more pronounced than U.S. scientists with relatively lower shares of stem cell research in their prior output. If the results were primarily driven by U.S. scientists exiting stem cell research, we would assume the scientists who had previously worked more intensively on hESC research would have the greatest amount of effort to re-allocate to other areas. While we do not deny that some scientists may have become disillusioned with stem cell research following the policy change, and this influenced their research direction, our results show that this is unlikely to have been the main causal driver for changes in research output among a substantial mass of scientists.

[12] One scientist who was managing an industry research lab at the time of the policy change told us that these scientists were particularly sought after as collaborators because of their knowledge isolating and culturing embryonic stem cells were valuable abilities carry out novel research in the emerging hESC research area.

6. Discussion and Conclusion

We develop a simple model that shows how an autonomous agent would change her allocation of effort across different projects in response to changes in the effort costs of securing resources for each project. The model generates two main predictions: (1) increasing the effort cost of securing resources for a project can, in certain circumstances, inadvertently reduce the share of effort allocated to other projects; and, (2) reducing the effort cost of securing resources for a project can, in certain circumstances, reduce the agents' share of effort allocated to that project and instead increase their share of effort allocated to other projects. The results stand in contrast to the naïve idea that reducing the relative effort required to secure resources for a project would increase the amount of effort invested in that project. Our model, though simple, shows the complexities associated with using resource-based incentive mechanisms as a tool to alter the allocation of agents' effort.

It is important to highlight some of the assumptions behind our model and potential avenues to extend it further. Our results are driven mainly by the fixed sunk cost of securing resources and diminishing returns to effort invested. We believe that these assumptions apply to a broad range of contexts. Of course, in practice, it is possible to shape the agents' allocation of effort through changes in the variable or fixed costs of production associated with each output. Such strategies would essentially be equivalent to changing the attractivity of projects relative to each other, i.e., γ_i, and can be directly incorporated into our model.

Moreover, in our model, the output from each project is independent of the amount of effort invested in securing the resources for it. In reality, it might be possible for agents to secure different levels or types of resources for a project depending on how much effort they initially invest in it. For example, they may decide to invest less effort and secure a lower-quality type of resource. Their output may then depend on the type or quality of secured resources. One way to map our model setup to this reality is to think of the effort cost of securing resources in our model as the minimum cost of entry into a certain project, task, or area. If agents allocate more effort to securing additional or better resources to improve their output, their additional effort can be considered as part of their productive effort spent on executing the project. Alternatively, it is possible to incorporate this added complexity by essentially modeling the decision to choose between two resource types or levels for a project as a decision to

invest in two mutually exclusive projects. In other words, an agent may either decide to invest in project A_h or A_l where the former requires more effort for securing resources and has a higher expected output per unit of productive effort (γ). Similarly, the agent can either invest in B_h or B_l (but not both) where the former is more costly and has a higher expected impact. It is possible then to model the problem as a more elaborate effort allocation across four possible projects where the agent can only invest in one type of each project. We hope future research sheds light on how such an extension affects the model predictions.

Further, in our model, agents cannot move resources secured for one project to another. Allowing the agents to shift resources from one project to another would require modeling the extent of resource redeployability and incorporating the agent's belief about the possibility of project failures and their additional choices. Also, the agent in our model faces a one-time simultaneous decision to allocate efforts between two projects. In reality, agents may choose first to invest some effort into one project and then decide how to proceed depending on the outcomes of their first decision.

Finally, we have modeled the choice of an agent to allocate a fixed amount of effort between different projects. What does happen if the agent could also choose their absolute level of effort? In such a scenario, the agent faces a two-stage decision. First, they need to decide how much total effort they want to invest in their projects versus, for example, spending their time on leisure activities. Next, they decide how to allocate their total effort between different projects. Our model is essentially concerned with the second step. The first-stage choice is explored and analyzed extensively in the field of economics. One could easily extend our model to a two-stage decision model with backward induction where the agent first calculates their optimal output as a function of their optimal allocation of effort between projects, and then decide about their total effort given the optimal output level and the utility of the alternative choice (e.g., leisure). We hope our model provides a stepping stone for future researchers to explore these extensions and contribute to our understanding of how resource-based incentive mechanisms affect agents' productivity and choice.

The model and its implications are particularly relevant to the context of academia. Recent research suggests that large corporations increasingly rely on scientific knowledge from academia as a key source of ideas for new innovations in their R&D processes (Cockburn and Henderson 1998,

Fabrizio 2009, Pisano 2010, Arora et al. 2018). Offering academic scientists easier or greater access to resources to conduct research on specific topics remains one of the primary levers used by external actors to steer scientists' research toward the topics deemed important to the sponsor. However, recent empirical work suggests that funding policies have limited effectiveness in changing scientists' research direction (Myers, 2020). Our model provides a possible theoretical explanation for these findings.

We test some of the model's predictions by examining the effect of a substantial change in funding for stem cell research in the U.S., introduced by the Bush administration in 2001, on the research direction of U.S. scientists. The change in the funding regime substantially increased the relative effort cost of securing resources for hESC research for U.S. scientists. In line with the model's predictions, we find that the hESC funding policy had a significant negative effect on U.S. scientists' non-hESC stem cell research output, compared with matched controls. We also find a negative effect on U.S. scientists' hESC output. However, the results on hESC output are mostly not significant and inconclusive. Importantly, aligned with our model's prediction, we find that more capable or reputable scientists were more likely to resist switching fields after the Bush policy change, and therefore experienced larger declines in their non-hESC output because of the policy.

While we only test our model in academia, in the context of stem cell research, the implications of the model go beyond the academic context. Resource-based incentives—i.e., incentivizing effort via changing the cost of securing resources—can be used as a substitute or complement to output-based and effort-based incentives. Past research generally points to norm-based or market-based incentive mechanisms when output-based and effort-based mechanisms are not feasible or effective. We show that it is still possible to affect agent's allocation of effort essentially via changing the sunk or entry cost of certain activities, essentially adding one more tool to the incentive toolbox that managers and policymakers can use to influence the agents' allocation of effort. Nevertheless, there is definitely more work that needs to be done. In particular, we need more research on when resource-based incentives should be used and how they interact with other incentive mechanisms. We hope that our paper sparks more research on these important topics.

Moreover, our findings speak directly to the literature on how firms can benefit from working with academic scientists, whether this is from sponsoring external research or collaborating on projects

(e.g., Cockburn and Henderson 1998, Cohen et al. 2002, Fabrizio 2009). Our model and empirical results highlight the challenges associated with steering the research direction of academic scientists through funding policies. Funding policies are mostly evaluated based on how they affect the level of research within their targeted domains. Our findings suggest that funding policies targeting certain scientific domains can have substantial spillover effects on related domains as well. Moreover, our model suggests that the scientists most able to make significant contributions at the knowledge frontier (to whom the reputational rewards are greatest from work on that topic) will require the largest resource inducement to switch topics. In contrast, those scientists who have lower expectations of their ability to contribute to the high-value field may be more willing to follow the resources if there is less marginal effect on their potential credit rewards from so doing.

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Tables and Figures

Table 1: Definitions of main variables

Variable	Description
U.S.-based between 1996 and 2000	Indicator variable equal to 1 if scientist *i* was based exclusively at U.S. institutions from 1996 to 2000 (inclusive)
Total Citation-Weighted Publications	The natural logarithm of one plus the total number of citations to scientist *i*'s publications in a given year *t*
SC Citation-Weighted Publications	The natural logarithm of one plus the total number of citations to scientist *i*'s publications in a stem cell field in a given year *t*
Non-SC Citation-Weighted Publications	The natural logarithm of one plus the total number of citations to scientist *i*'s publications that are not in a stem cell field a given year *t*
Non-hESC SC Citation-Weighted Publications	The natural logarithm of one plus the total number of citations to scientist *i*'s publications in a non-hESC sub-field of stem cell research in a given year *t*
hESC Citation-Weighted Publications	The natural logarithm of one plus the total number of citations to scientist *i*'s publications in the hESC sub-field of stem cell research in a given year *t*
Has ESC Publication Pre-2001	Indicator variable equal to 1 if scientist *i* had a publication involving embryonic stem cell research in a year strictly prior to 2001
SC Citation Share between 1996 and 2000	The share of all citations to scientist *i*'s papers published from 1996 to 2000 (inclusive) that were to scientist *i*'s papers in a stem cell field
Total Citations between 1996 and 2000	The total number of citations received by scientist *i*'s papers published from 1996 to 2000 (inclusive)
Has Industry Affiliation	Indicator variable equal to 1 if scientist *i* had an industry affiliation in year *t*
Has University/Hospital Affiliation	Indicator variable equal to 1 if scientist *i* had a university or health service provider affiliation in year *t*
Publication Involves Industry Collaboration	Indicator variable equal to 1 if a publication by scientist *i* in year *t* involves a coauthor with an industry affiliation
Publication Involves non-hESC SC Industry Collab	Indicator variable equal to 1 if a publication by scientist *i* in year *t* is in a non-hESC sub-field of stem cell research and involves a coauthor with an industry affiliation
Publication Involves hESC Industry Collab	Indicator variable equal to 1 if a publication by scientist *i* in year *t* is in the hESC sub-field of stem cell research and involves a coauthor with an industry affiliation
Publication Involves Int Flex Collab	Indicator variable equal to 1 if a publication by scientist *i* in year *t* involves a coauthor from a country with a flexible hESC funding regime
Publication Involves non-hESC SC Int Flex Collab	Indicator variable equal to 1 if a publication by scientist *i* in year *t* is in a non-hESC sub-field of stem cell research and involves a coauthor from a country with a flexible hESC funding regime
Publication Involves hESC Int Flex Collab	Indicator variable equal to 1 if a publication by scientist *i* in year *t* is in the hESC sub-field of stem cell research and involves a coauthor from a country with a flexible hESC funding regime

Notes: To be included in the sample, a scientist must have been based exclusively in either the U.S. or one of our control countries. Therefore, the zero value of the indicator variable defined in the first row of the table denotes a scientist who was based exclusively at institutions in a control country from 1996 to 2000 (inclusive). Where we do not observe an affiliation or collaboration for scientist *i* from a publication in a given year *t*, we interpolate using the most proximate observation of that variable to fill the missing observations for the final five variables listed in the table. For the 5 (full sample) and 4 (matched sample) scientists who have stem cell publications but no citations in the 1996-2000 period, we replace the citation share observations with the share of scientist *i*'s publications that were in a stem cell field during this period.

Table 2: Summary statistics

Panel A: Full sample

Variable	Obs	Mean	Std Dev	Min	Max
U.S.-based Scientist	120,918	0.711	0.453	0	1
Year of First Publication	120,918	1990.4	6.593	1976	2000
Year of First SC Publication	120,918	1996.9	3.213	1980	2000
Citation-Weighted Pubs	120,918	83.25	253.3	0	16,488
Ln(Citation-Weighted Pubs+1)	120,918	2.138	2.287	0	9.710
Stem Cell Citation-Weighted Pubs	120,918	14.23	102.9	0	8274
Ln(SC Citation-Weighted Pubs+1)	120,918	0.554	1.397	0	9.021
Non-Stem Cell Citation-Weighted Pubs	120,918	69.02	223.1	0	16,488
Ln(non-SC Citation-Weighted Pubs+1)	120,918	1.882	2.224	0	9.710
Non-hESC SC Citation-Weighted Pubs	120,918	13.77	101.2	0	8,274
Ln(non-hESC SC Citation-Weighted Pubs+1)	120,918	0.544	1.383	0	9.021
hESC Citation-Weighted Pubs	120,918	0.465	15.14	0	1,919
Ln(hESC Citation-Weighted Pubs+1)	120,918	0.014	0.250	0	7.560
Has ESC Publication Pre-2001	120,918	0.188	0.390	0	1
SC Citations Share 1996-2000	120.918	0.383	0.357	0	1
Has Industry Affiliation	120,805	0.114	0.318	0	1
Has University/Hospital Affiliation	120,805	0.914	0.280	0	1
Pub Involves Industry Collab	65,226	0.247	0.431	0	1
Pub Involves non-hESC SC Industry Collab	66,446	0.038	0.192	0	1
Pub Involves hESC Industry Collab	66,749	0.002	0.046	0	1
Pub Involves Int Flex Collab	64,814	0.269	0.443	0	1
Pub Involves non-hESC SC Int Flex Collab	66,544	0.038	0.190	0	1
Pub Involves hESC Int Flex Collab	66,752	0.002	0.044	0	1

Panel B: Matched sample

Variable	Obs	Mean	Std Dev	Min	Max
U.S.-based Scientist	71,596	0.612	0.487	0	1
Year of First Publication	71,596	1992.1	6.129	1976	2000
Year of First SC Publication	71,596	1997.6	2.428	1980	2000
Citation-Weighted Pubs	71,596	31.87	90.75	0	4,823
Ln(Citation-Weighted Pubs+1)	71,596	1.555	1.949	0	8.481
Stem Cell Citation-Weighted Pubs	71,596	5.662	41.31	0	4,613
Ln(SC Citation-Weighted Pubs+1)	71,596	0.391	1.112	0	8.437
Non-Stem Cell Citation-Weighted Pubs	71,596	26.21	78.31	0	4,598
Ln(non-SC Citation-Weighted Pubs+1)	71,596	1.330	1.866	0	8
Non-hESC SC Citation-Weighted Pubs	71,596	5.518	40.83	0	4,613
Ln(non-hESC SC Citation-Weighted Pubs+1)	71,596	0.386	1.104	0	8
hESC Citation-Weighted Pubs	71,596	0.145	5.821	0	487
Ln(hESC Citation-Weighted Pubs+1)	71,596	0.007	0.162	0	6
Has ESC Publication Pre-2001	71,596	0.101	0.301	0	1
SC Citations Share 1996-2000	71,532	0.436	0.370	0	1
Has Industry Affiliation	71,544	0.059	0.236	0	1
Has University/Hospital Affiliation	71,544	0.957	0.203	0	1
Pub Involves Industry Collab	32,258	0.163	0.369	0	1
Pub Involves non-hESC SC Industry Collab	33,066	0.026	0.159	0	1
Pub Involves hESC Industry Collab	33,252	0.001	0.033	0	1
Pub Involves Int Flex Collab	32,239	0.205	0.404	0	1
Pub Involves non-hESC SC Int Flex Collab	33,135	0.030	0.172	0	1
Pub Involves hESC Int Flex Collab	33,252	0.001	0.035	0	1

Table 3: Test of pre-shock differences in publications and affiliations between U.S. and control scientists (1996-2000 inclusive)

Panel A: Full sample

Variable	Control Scientists	U.S. Scientists	T-Test Difference
Number of Scientists	2,231	5,479	-
Number of Scientist-Year Observations	9,813	24,574	-
Year of First Publication	1989.9	1989.4	-0.483***
Year of First SC Publication	1996.8	1996.7	-0.140***
Ln(Total Citation-Weighted Publications+1)	2.820	3.305	0.485***
Ln(SC Citation-Weighted Publications+1)	0.968	1.140	0.172***
Ln(Non-SC Citation-Weighted Publications+1)	2.299	2.748	0.449***
Ln(Non-hESC SC Citation-Weighted Publications+1)	0.968	1.139	0.171***
Ln(hESC Citation-Weighted Publications+1)	0.000	0.002	0.002
Has Industry Affiliation	0.036	0.123	0.087***
Has University/Hospital Affiliation	0.978	0.909	-0.069**
Has ESC Publication Pre-2001	0.118	0.219	0.101***

Panel B: Matched sample

Variable	Control Scientists	U.S. Scientists	T-Test Difference
Number of Scientists	1,781	2,824	-
Number of Scientist-Year Observations	7,645	11,908	-
Year of First Publication	1991.3	1991.3	-0.018
Year of First SC Publication	1997.4	1997.4	0.002
Ln(Total Citation-Weighted Publications+1)	2.402	2.402	0.000
Ln(SC Citation-Weighted Publications+1)	0.888	0.898	0.010
Ln(Non-SC Citation-Weighted Publications+1)	1.857	1.831	-0.026
Ln(Non-hESC SC Citation-Weighted Publications+1)	0.888	0.898	0.010
Ln(hESC Citation-Weighted Publications+1)	0.000	0.000	0.000
Has Industry Affiliation	0.041	0.042	0.001
Has University/Hospital Affiliation	0.971	0.969	-0.002
Has ESC Publication Pre-2001	0.112	0.112	0.000

Notes: We use the weighting procedure used in the regression analysis to generate the test statistics for the matched sample. A similarly weighted version of the summary statistics in Table 2 is available from the authors upon request. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Impact of the Bush hESC policy on U.S. scientists' research direction and output

Panel A: Full sample

	(1)	(2)	(3)	(4)	(5)
	All Pubs	SC Pubs	Non-SC Pubs	Non-hESC SC Pubs	hESC Pubs
US Author * T0205	-0.125*** (0.035)	-0.131*** (0.024)	-0.063* (0.035)	-0.127*** (0.024)	-0.007 (0.005)
US Author * T0609	-0.221*** (0.039)	-0.128*** (0.025)	-0.169*** (0.039)	-0.124*** (0.024)	0.001 (0.007)
US Author * T1012	-0.346*** (0.036)	-0.159*** (0.021)	-0.300*** (0.039)	-0.156*** (0.020)	-0.003 (0.004)
Scientist FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	104,338	104,338	104,338	104,338	98,796
Within R^2	0.192	0.076	0.133	0.078	0.003
Scientists	6,662	6,662	6,662	6,662	6,662

Panel B: Matched sample

	(1)	(2)	(3)	(4)	(5)
	All Pubs	SC Pubs	Non-SC Pubs	Non-hESC SC Pubs	hESC Pubs
US Author * T0205	-0.054 (0.045)	-0.101*** (0.028)	0.029 (0.044)	-0.097*** (0.027)	-0.006 (0.005)
US Author * T0609	-0.115** (0.049)	-0.079*** (0.029)	-0.056 (0.048)	-0.069** (0.028)	-0.008 (0.008)
US Author * T1012	-0.089** (0.045)	-0.051** (0.023)	-0.049 (0.046)	-0.044* (0.023)	-0.008 (0.005)
Scientist FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	67,796	67,796	67,796	67,796	64,393
Within R^2	0.139	0.081	0.083	0.083	0.002
Scientists	4,360	4,360	4,360	4,360	4,360

Notes: All estimates are based on panel OLS regression with year and scientist fixed effects. The dependent variable is the natural logarithm of 1 plus the total number of citation-weighted publications in the relevant research area. All scientists with an industry affiliation in the pre-shock period are excluded. The 1997–2012 period is used for Models 1 through 4. Model 5 limits the window to 1998–2012 since this was the year in which the Thomson lab first published the technique for deriving hESCs, changing the incentives for researchers to enter this sub-field. Constant term included in the regression but not reported in the table. Standard errors (in parentheses) are clustered at the scientist level to allow for serial correlation and are robust to arbitrary heteroskedasticity. SC: stem cell research; hESC: stem cell research involving human embryonic stem cells; non-hESC SC: stem cell research not involving human embryonic stem cells; Non-SC: research outside stem cell fields. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Changes in U.S. scientists' research direction and output by pre-shock output

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All Pubs		SC Pubs		Non-SC Pubs		Non-hESC SC Pubs		hESC Pubs	
	Low Cites 96-00	*High Cites 96-00*	*Low Cites 96-00*	*High Cites 96-00*	*Low Cites 96-00*	*High Cites 96-00*	*Low Cites 96-00*	*High Cites 96-00*	*Low Cites 96-00*	*High Cites 96-00*
US Author * T0205	-0.016	-0.055	-0.051*	-0.187***	0.034	0.102	-0.048	-0.179***	-0.006	-0.009
	(0.049)	(0.095)	(0.030)	(0.063)	(0.046)	(0.092)	(0.029)	(0.061)	(0.005)	(0.013)
US Author * T0609	-0.045	-0.148	-0.045	-0.118*	-0.001	-0.068	-0.033	-0.115*	-0.010	-0.003
	(0.053)	(0.101)	(0.030)	(0.068)	(0.052)	(0.096)	(0.028)	(0.067)	(0.010)	(0.014)
US Author * T1012	-0.031	-0.048	-0.036	-0.036	0.013	-0.029	-0.029	-0.029	-0.008	-0.010
	(0.049)	(0.083)	(0.023)	(0.054)	(0.050)	(0.089)	(0.023)	(0.054)	(0.006)	(0.009)
Scientist FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	47,164	20,632	47,164	20,632	47,164	20,632	47,164	20,632	44,694	19,699
Within R^2	0.102	0.234	0.071	0.109	0.058	0.158	0.073	0.112	0.002	0.004
Scientists	3,017	1,343	3,017	1,343	3,017	1,343	3,017	1,343	3,017	1,343

Notes: All estimates are based on panel OLS regression with year and scientist fixed effects. The dependent variable is the natural logarithm of 1 plus the total number of citation-weighted publications in the relevant research area. The sample is split according to whether scientists have greater or strictly fewer than the median number of citations in the five years prior to the policy change (1996-2000) relative to other scientists in the full sample whose first publication was observed in the same year. All scientists with an industry affiliation in the pre-shock period are excluded. The 1997–2012 period is used for Models 1 through 8. Models 9 and 10 limits the window to 1998–2012 for reason given in the notes to Table 4. Constant term included in the regression but not reported in the table. Constant term included in the regression but not reported in the table. Standard errors (in parentheses) are clustered at the scientist level to allow for serial correlation and are robust to arbitrary heteroskedasticity. SC: stem cell research; hESC: stem cell research involving human embryonic stem cells; non-hESC SC: stem cell research not involving human embryonic stem cells; Non-SC: research outside stem cell fields. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Changes in U.S. scientists' institutional affiliations following the Bush policy change

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Has Industry Affiliation				Has University/Hospital Affiliation			
	All	*SC Cite Share ≤0.666*	*SC Cite Share >0.666*	*SC Cite Share >0.666, >1 Pub*	*All*	*SC Cite Share ≤0.666*	*SC Cite Share >0.666*	*SC Cite Share >0.666, >1 Pub*
US Author * T0205	0.010*	0.007	0.019**	0.024**	-0.003	0.001	-0.015*	-0.026***
	(0.006)	(0.008)	(0.009)	(0.010)	(0.005)	(0.006)	(0.008)	(0.008)
US Author * T0609	0.012*	0.009	0.021**	0.034***	-0.006	-0.002	-0.018**	-0.035***
	(0.007)	(0.009)	(0.010)	(0.011)	(0.005)	(0.007)	(0.009)	(0.009)
US Author * T1012	0.016**	0.011	0.030***	0.038***	-0.011**	-0.006	-0.025***	-0.038***
	(0.007)	(0.009)	(0.011)	(0.012)	(0.006)	(0.007)	(0.009)	(0.010)
Scientist FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	71,544	49,930	21,614	14,386	71,544	49,930	21,614	14,386
Within R^2	0.011	0.012	0.010	0.013	0.011	0.012	0.010	0.013
Scientists	4,601	3,157	1,444	924	4,601	3,157	1,444	924

Notes: All estimates are based on panel OLS regression with year and scientist fixed effects. The samples are split according to whether scientists received more than 66.6 percent of their citations to publications in stem cell research during the 1996–2000 period. Since only scientists with at least one stem cell publication are included in our sample, all scientists with only one publication are in the sub-sample of scientists who received more than 66.6 percent of their citations to publications in stem cell research during the 1996–2000 period. There are four matched scientists in our sample who have no citations (but do have publications) during the pre-shock period. We use the scientists' share of publications that were in stem cell research in place of the citation-based variable for these scientists. Constant term included in the regression but not reported in the table. Standard errors (in parentheses) are clustered at the scientist level to allow for serial correlation and are robust to arbitrary heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1.

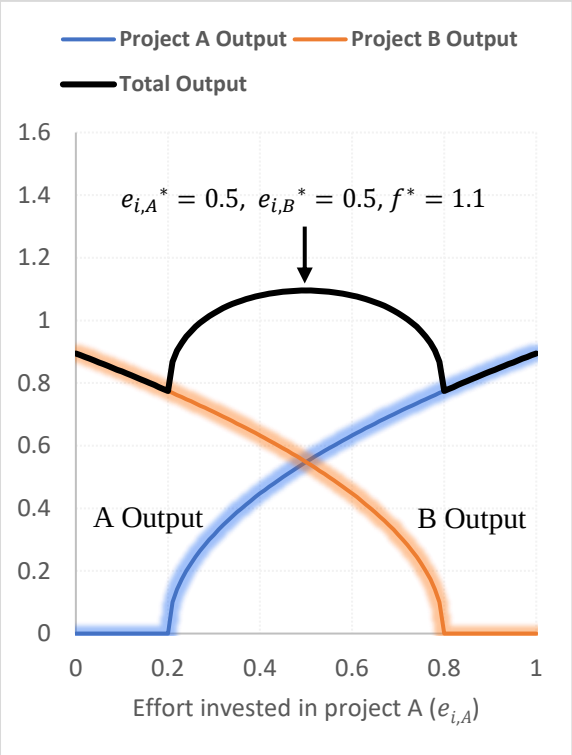
Table 7: Changes in the collaborative profile of U.S. scientists' publications following the Bush policy change

	(1)	(2)	(3)	(4)	(5)	(6)
	Pub Involves hESC Industry Collab	Pub Involves non-hESC SC Industry Collab	Pub Involves Industry Collab	Pub Involves hESC Int Flex Collab	Pub Involves non-hESC SC Int Flex Collab	Pub Involves Int Flex Collab
US Author *	0.001**	-0.012**	-0.022*	0.000	-0.016**	-0.037**
T0205	(0.001)	(0.005)	(0.011)	(0.001)	(0.007)	(0.014)
US Author *	0.002	-0.011**	-0.011	-0.000	-0.007	-0.027*
T0609	(0.001)	(0.005)	(0.013)	(0.001)	(0.007)	(0.016)
US Author *	-0.003	-0.014**	-0.037**	-0.006**	-0.011	-0.020
T1012	(0.002)	(0.006)	(0.015)	(0.003)	(0.009)	(0.020)
Scientist FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	29,500	29,347	28,610	29,507	29,398	28,587
Within R^2	0.005	0.003	0.077	0.002	0.001	0.034
Scientists	4,120	4,116	4,108	4,124	4,122	4,117

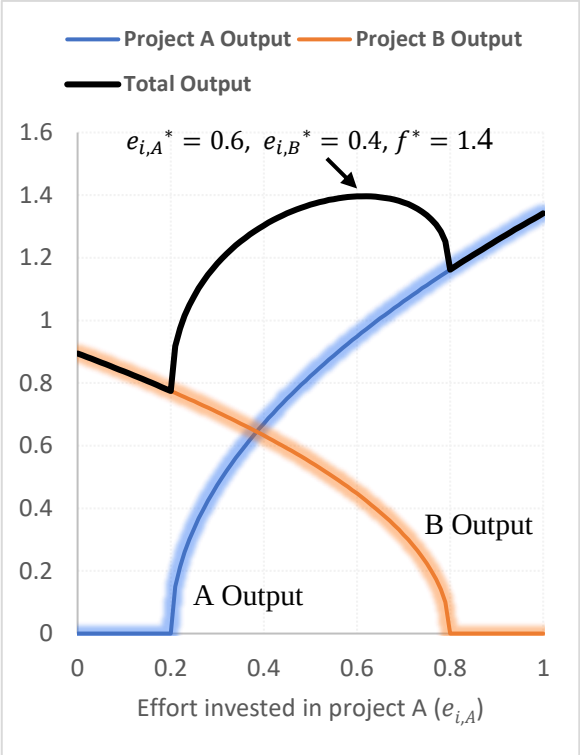
Notes: All estimates are based on panel OLS regression with scientist fixed effects and time period fixed effects for the 2002–2005, 2006–2009, and 2010–2012 periods (with 1998–2001 the omitted time-period dummy variable). The dependent variable is only observed if in year *t* scientist *i* has a publication. The period in the analysis is 1998–2012 inclusive. Models 1 to 3 include a control variable measuring whether a scientist *i* had an industry affiliation in year *t*. SC: stem cell research; hESC: stem cell research involving human embryonic stem cells; non-hESC SC: stem cell research not involving human embryonic stem cells. Constant term included in the regression but not reported in the table. Standard errors (in parentheses) are clustered at the scientist level to allow for serial correlation and are robust to arbitrary heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Numerical examples based on the formal model

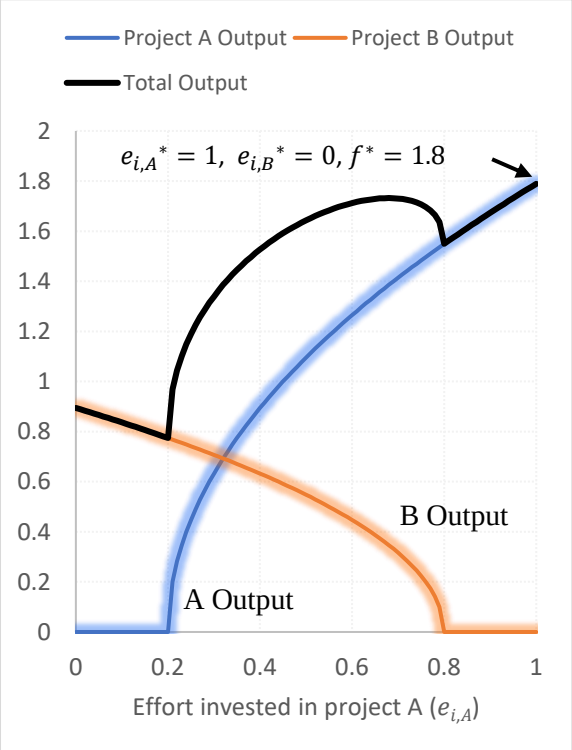
Panel A: $\alpha_i = \beta_i = 0.2, \gamma_{i,A} = \gamma_{i,B} = 1$



Panel B: $\alpha_i = \beta_i = 0.2, \gamma_{i,A} = 1.5,\ \gamma_{i,B} = 1$



Panel C: $\alpha_i = \beta_i = 0.2, \gamma_{i,A} = 2,\ \gamma_{i,B} = 1$



Panel D: $\alpha_i = 0.2,\ \beta_i = 0.5, \gamma_{i,A} = 1.5,\ \gamma_{i,B} = 1$

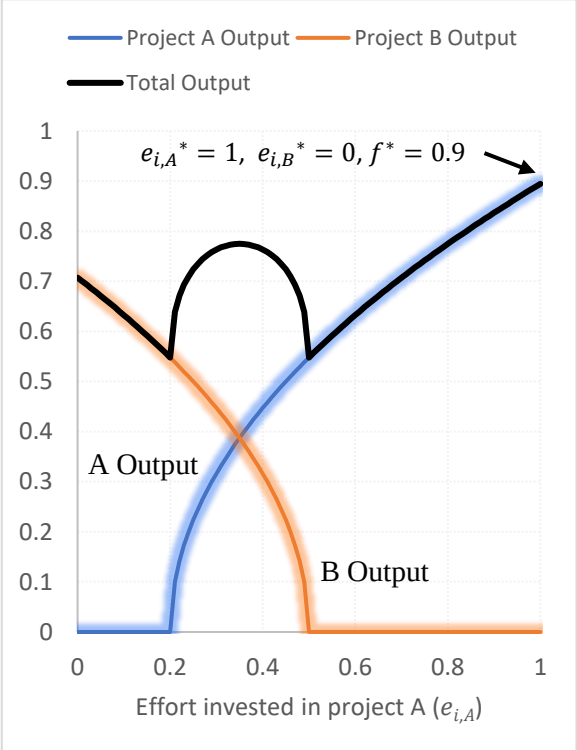
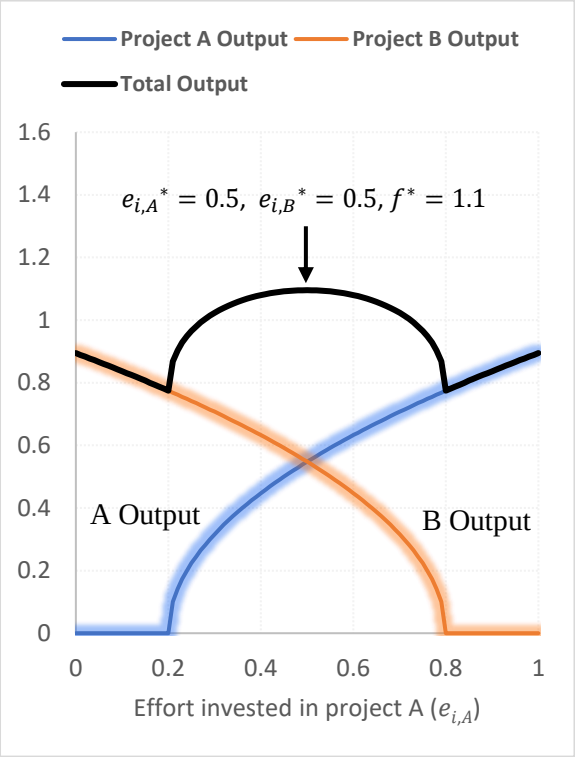
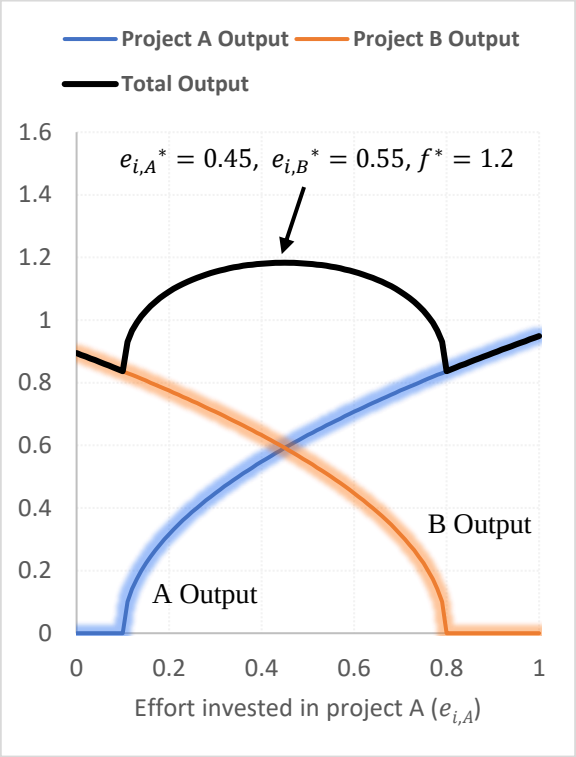


Figure 2- Changes in the optimal allocation of effort with respect to changes in the cost of securing resources for project A

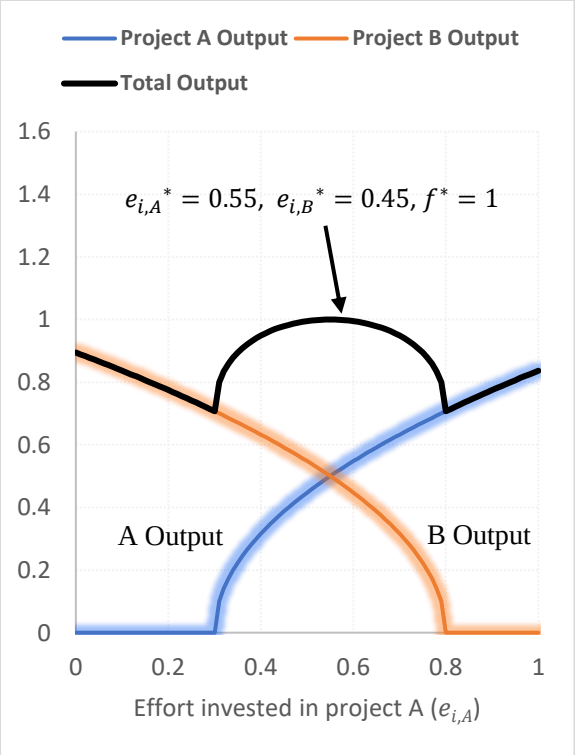
Panel A: $\alpha_i = \beta_i = 0.2, \gamma_{i,A} = \gamma_{i,B} = 1$



Panel B: $\alpha_i = 0.1,\ \beta_i = 0.2, \gamma_{i,A} = \gamma_{i,B} = 1$



Panel C: $\alpha_i = 0.3,\ \beta_i = 0.2, \gamma_{i,A} = \gamma_{i,B} = 1$



Panel D: $\alpha_i = 0.5,\ \beta_i = 0.2, \gamma_{i,A} = \gamma_{i,B} = 1$

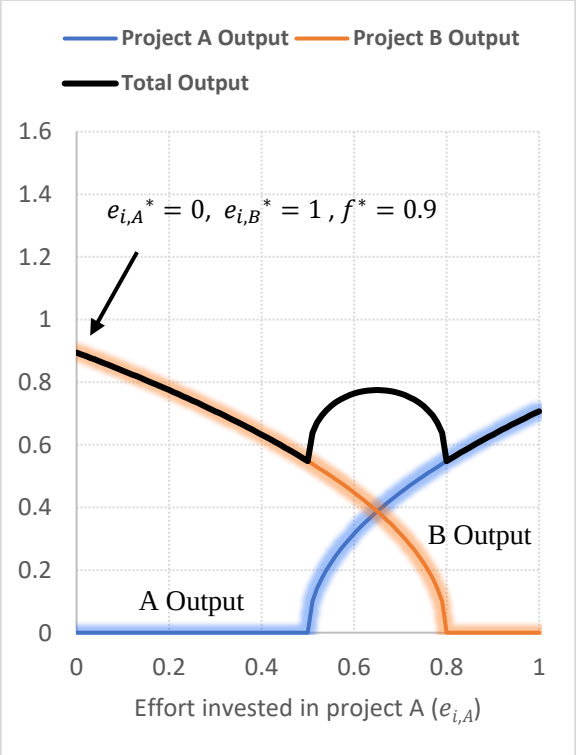
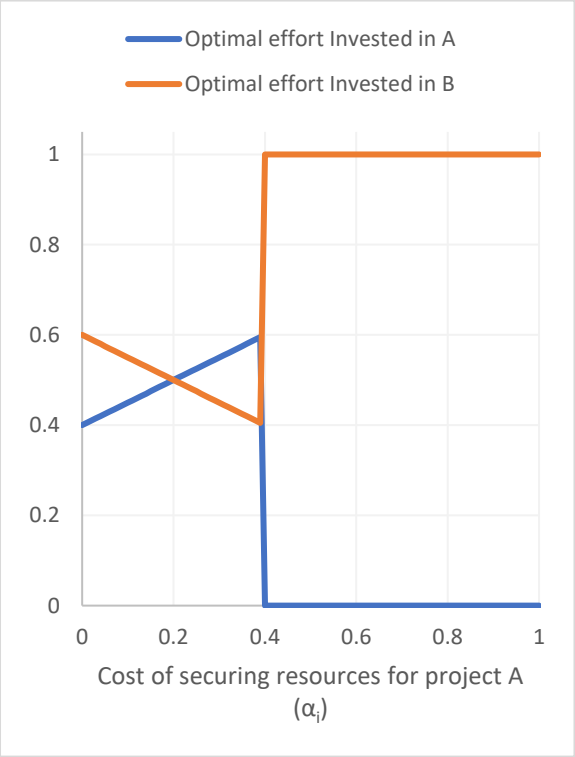
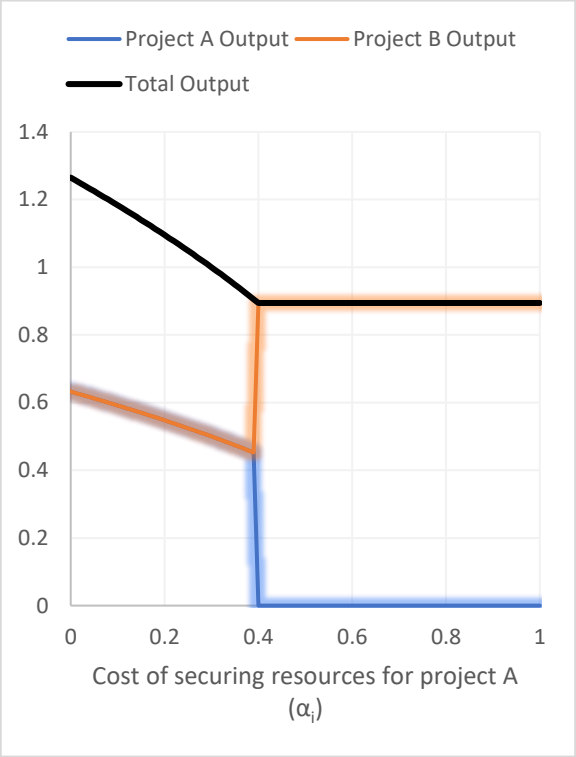


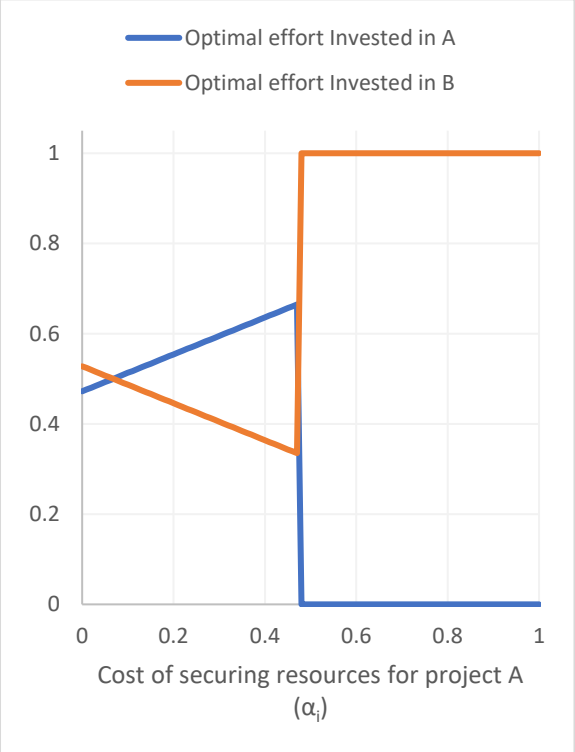
Figure 3- Changes in the optimal effort allocation and the optimal output with respect to changes in the cost of securing resources for project A

Panel A: $\beta_i = 0.2, \gamma_{i,A} = \gamma_{i,B} = 1$





Panel B: $\beta_i = 0.2, \gamma_{i,A} = 1.2, \ \gamma_{i,B} = 1$



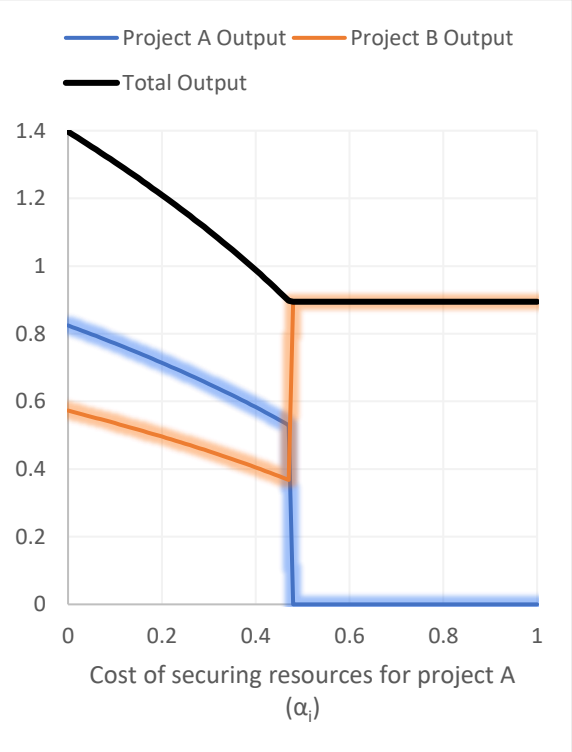
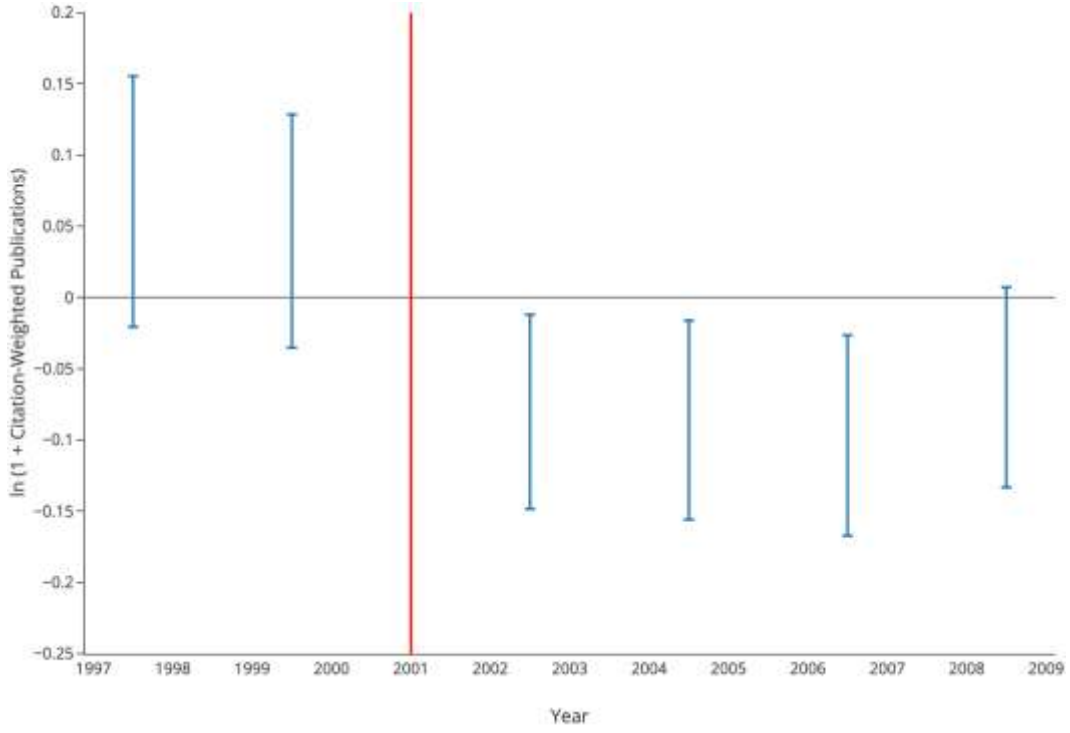
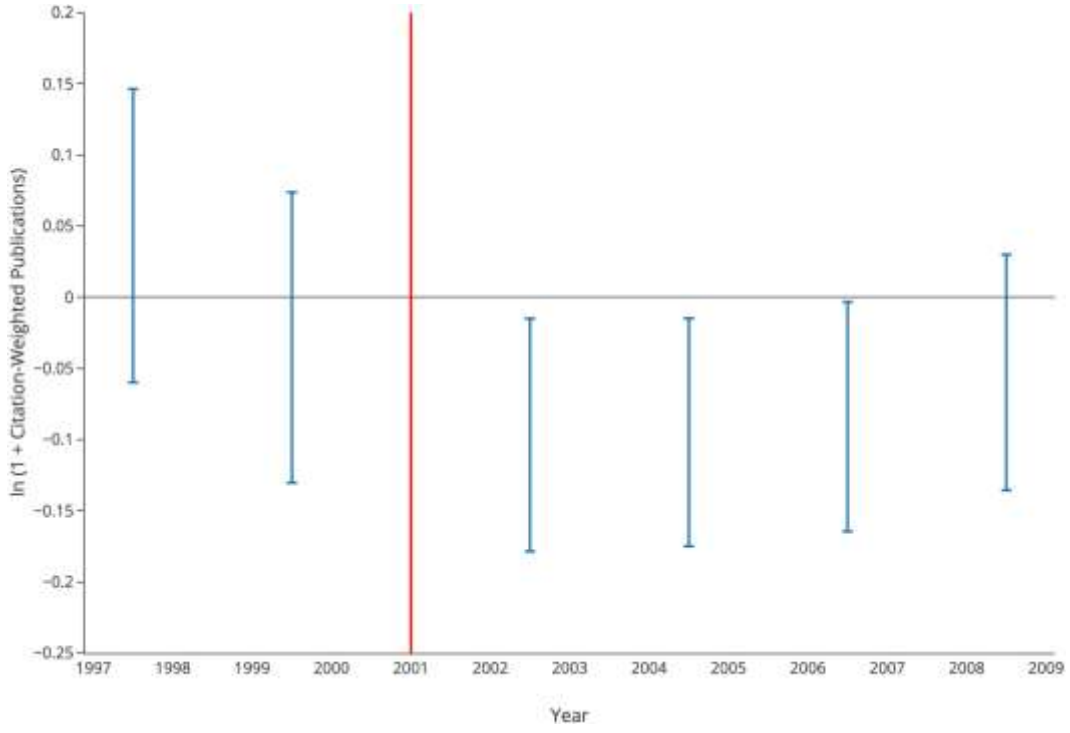


Figure 4: Impact of the Bush policy on U.S. scientists' research direction and output

Panel A: Changes in non-hESC stem cell research citation-weighted publications (full sample)



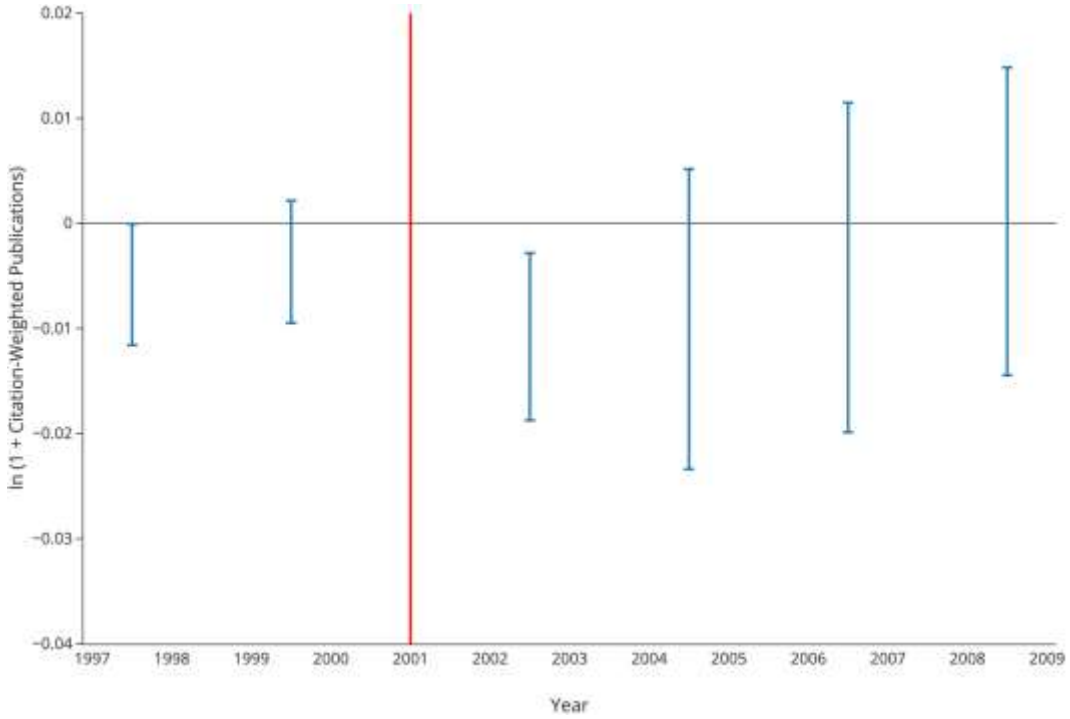
Panel B: Changes in non-hESC stem cell research citation-weighted publications (matched sample)



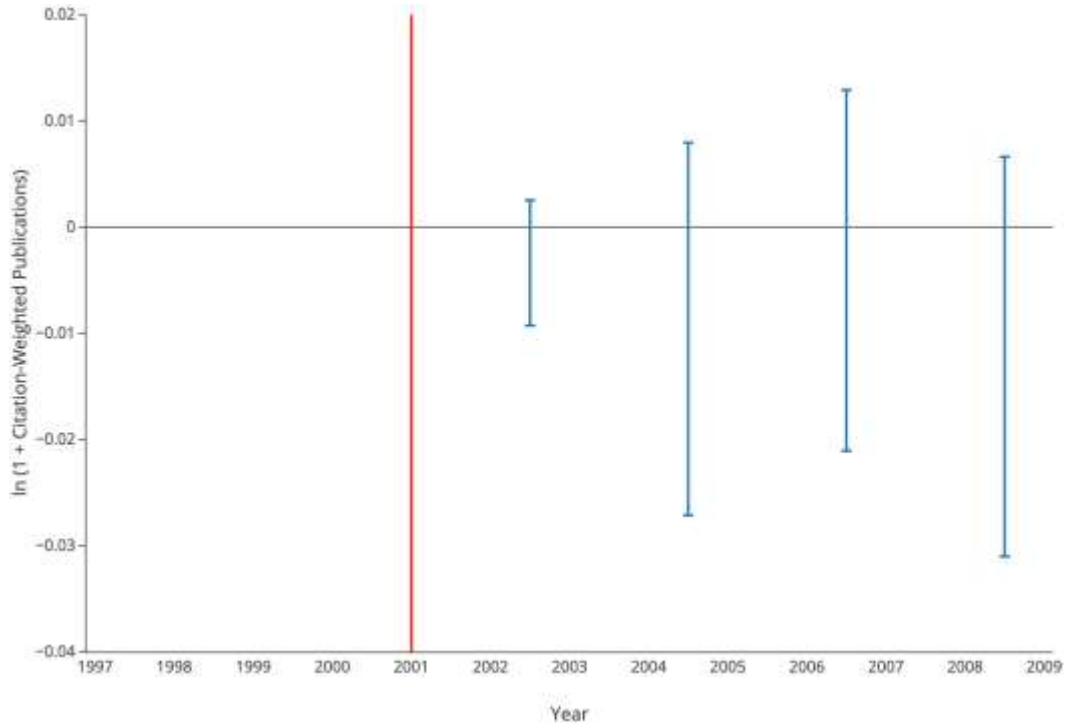
Notes: Figures show the results from Scientist FE models. Years are grouped into two-year periods with the exception of the base year, 2001. Scientists with a pre-shock industry affiliation are excluded from the analysis.

Figure 5: Impact of the Bush policy on U.S. scientists' hESC research output

Panel A: Changes in hESC citation-weighted publications (full sample)



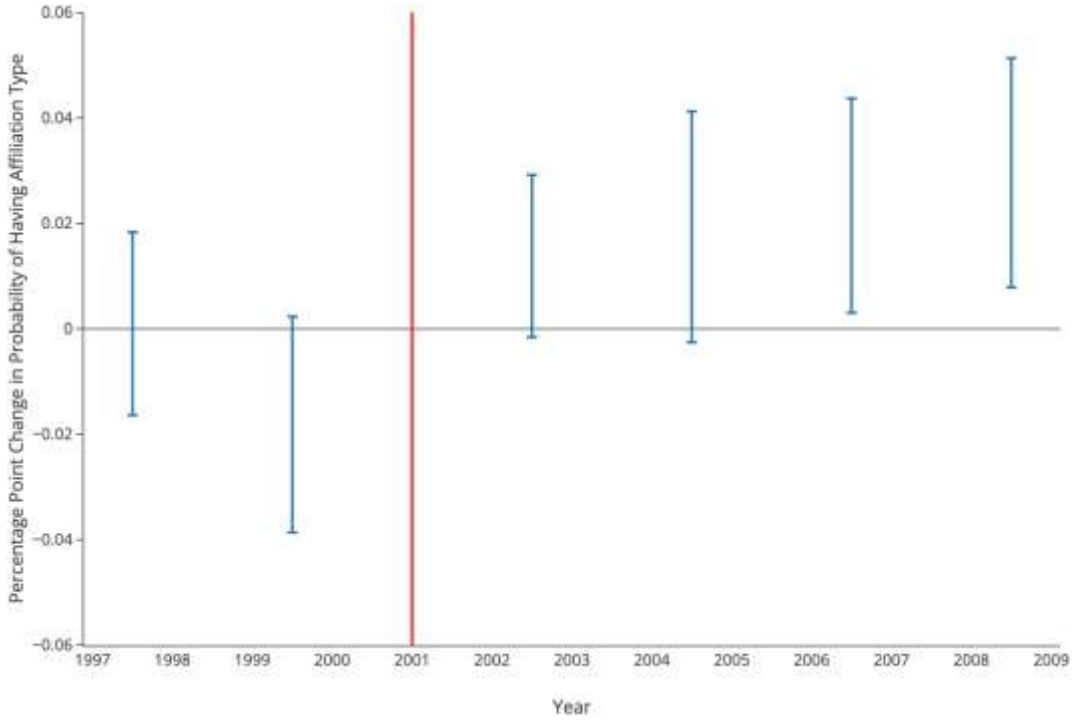
Panel B: Changes in hESC citation-weighted publications (matched sample)



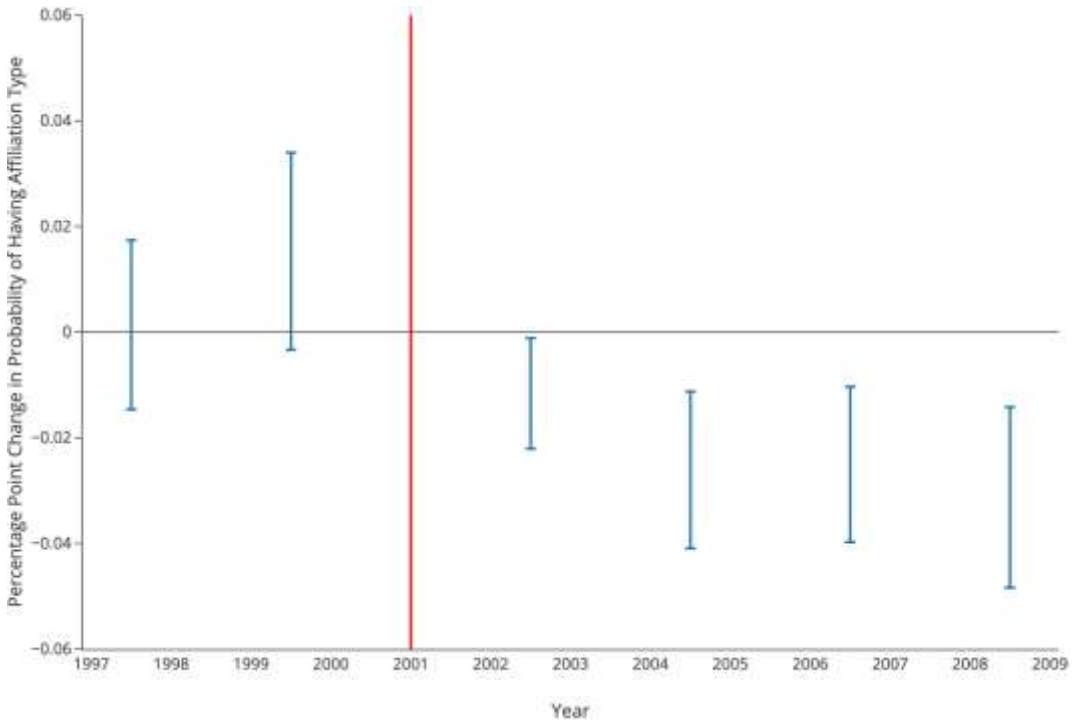
Notes: Figures show the results from Scientist FE models. Due to the paucity of hESC publications among matched scientists in the pre-shock period we do not include these separately on the graph (however, if included they are not significantly different from those in the base year) Years are grouped into two-year periods with the exception of the base year, 2001. Scientists with a pre-shock industry affiliation are excluded from the analysis.

Figure 6: Impact of the Bush hESC policy on U.S. scientists' institutional affiliations

Panel A: Changes in U.S. scientists' probability of having an industry affiliation



Panel B: Changes in U.S. scientists' probability of having a university or hospital affiliation



Notes: Figures show the results from models that follow the specifications in Models 4 and 8 of Table 2.5. Years are grouped into two-year periods with the exception of the base year, 2001

Online Appendix

Incentivizing effort allocation through resource allocation: Evidence from scientists' response to changes in funding policy

Tables and Figures

Table A.1: Heterogeneity of Bush policy impact based on prior investment in stem cell research

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All Pubs		SC Pubs		Non-SC Pubs		Non-hESC SC Pubs		hESC Pubs	
	SC Cite Share <0.5	*SC Cite Share ≥0.5*	*SC Cite Share <0.5*	*SC Cite Share ≥0.5*	*SC Cite Share <0.5*	*SC Cite Share ≥0.5*	*SC Cite Share <0.5*	*SC Cite Share ≥0.5*	*SC Cite Share <0.5*	*SC Cite Share ≥0.5*
US Author * T0205	-0.053	-0.070	-0.097***	-0.101**	0.020	0.019	-0.093***	-0.096**	-0.002	-0.013
	(0.059)	(0.069)	(0.034)	(0.049)	(0.057)	(0.060)	(0.033)	(0.048)	(0.005)	(0.011)
US Author * T0609	-0.062	-0.212***	-0.051	-0.115**	-0.027	-0.128*	-0.050	-0.090*	0.002	-0.024
	(0.061)	(0.080)	(0.033)	(0.055)	(0.059)	(0.068)	(0.032)	(0.050)	(0.006)	(0.019)
US Author * T1012	-0.067	-0.149**	-0.026	-0.084*	-0.044	-0.094*	-0.025	-0.067	-0.002	-0.018*
	(0.053)	(0.071)	(0.025)	(0.047)	(0.054)	(0.056)	(0.025)	(0.047)	(0.005)	(0.010)
Scientist FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	42,354	25,442	42,354	25,442	42,354	25,442	42,354	25,442	39,948	24,445
Within R^2	0.180	0.079	0.056	0.134	0.140	0.033	0.057	0.138	0.002	0.004
Scientists	2,674	1,686	2,674	1,686	2,674	1,686	2,674	1,686	2,674	1,686

Notes: All estimates are based on panel OLS regression with year and scientist fixed effects. The dependent variable is the natural logarithm of 1 plus the total number of citation-weighted publications in the relevant research area. In Models 1 through 10, the sample is split according to whether scientists received more than half their citations to publications in stem cell research during the 1996–2000 period. There are four matched scientists in our sample who have no citations (but do have publications) during the pre-shock period. We use the scientists' share of publications that were in stem cell research in place of the citation-based variable for these scientists. All scientists with an industry affiliation in the pre-shock period are excluded. The 1997–2012 period is used for Models 1 through 4. Model 5 limits the window to 1998–2012 since this was the year in which the Thomson lab first published the technique for deriving hESCs, changing the incentives for researchers to enter this sub-field. Constant term included in the regression but not reported in the table. Standard errors (in parentheses) are clustered at the scientist level to allow for serial correlation and are robust to arbitrary heteroskedasticity. SC: stem cell research; hESC: stem cell research involving human embryonic stem cells; non-hESC SC: stem cell research not involving human embryonic stem cells; Non-SC: research outside stem cell fields. *** p<0.01, ** p<0.05, * p<0.1.

Table A.2: Impact of the Bush hESC policy on U.S. scientists' raw publication counts

	(1)	(2)	(3)	(4)	(5)
	All Pubs	SC Pubs	Non-SC Pubs	Non-hESC SC Pubs	hESC Pubs
US Author *	0.007	-0.014**	0.021	-0.013**	-0.001
T0205	(0.013)	(0.007)	(0.013)	(0.006)	(0.001)
US Author *	0.009	-0.006	0.016	-0.004	-0.002
T0609	(0.017)	(0.008)	(0.016)	(0.007)	(0.002)
US Author *	-0.001	-0.004	0.005	-0.001	-0.004*
T1012	(0.019)	(0.007)	(0.019)	(0.007)	(0.002)
Scientist FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	67,796	67,796	67,796	67,796	64,393
Within R^2	0.036	0.069	0.009	0.072	0.003
Scientists	4,360	4,360	4,360	4,360	4,360

Notes: All estimates are based on panel OLS regression with year and scientist fixed effects. The dependent variable is the natural logarithm of 1 plus the total number of publications in the relevant research area. All scientists with an industry affiliation in the pre-shock period are excluded. The 1997–2012 period is used for Models 1 through 4. Model 5 limits the window to 1998–2012 for the reasons given in the notes to Table 4. Constant term included in the regression but not reported in the table. Standard errors (in parentheses) are clustered at the scientist level to allow for serial correlation and are robust to arbitrary heteroskedasticity. SC: stem cell research; hESC: stem cell research involving human embryonic stem cells; non-hESC SC: stem cell research not involving human embryonic stem cells; Non-SC: research outside stem cell fields. *** p<0.01, ** p<0.05, * p<0.1.

Table A.3: Impact of Bush policy on U.S. scientists' probability of having high impact publications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Has Top 20% Publication			*Has Top 10% Publication*			*Has Top 5% Publication*		
	All Pubs	Non-hESC SC Pubs	hESC Pubs	All Pubs	Non-hESC SC Pubs	hESC Pubs	All Pubs	Non-hESC SC Pubs	hESC Pubs
US Author * T0205	-0.019**	-0.013***	0.000	-0.002	-0.003	0.000	0.006*	-0.000	0.000*
	(0.007)	(0.004)	(0.000)	(0.005)	(0.002)	(0.000)	(0.003)	(0.001)	(0.000)
US Author * T0609	-0.039***	-0.013***	-0.001	-0.008	-0.003*	-0.000	0.000	-0.000	0.000
	(0.009)	(0.004)	(0.001)	(0.006)	(0.002)	(0.000)	(0.004)	(0.001)	(0.000)
US Author * T1012	-0.035***	-0.012***	-0.001	-0.010*	-0.006**	0.000	-0.005	-0.004**	0.000
	(0.008)	(0.004)	(0.001)	(0.006)	(0.002)	(0.000)	(0.004)	(0.002)	(0.000)
Scientist FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	67,796	67,796	64,393	67,796	67,796	64,393	67,796	67,796	64,393
Within R^2	0.003	0.004	0.001	0.004	0.001	0.000	0.005	0.001	0.000
Scientists	4,360	4,360	4,360	4,360	4,360	4,360	4,360	4,360	4,360

Notes: All estimates are based on panel OLS regression with year and scientist fixed effects. The dependent variables are indicator variables that note whether a scientist has a publication that is among the top 20%, 10%, or 5% of publications by number of citations in the relevant research area in a given year. Standard errors (in parentheses) are clustered at the scientist level to allow for serial correlation and are robust to arbitrary heteroskedasticity. SC: stem cell research; hESC: stem cell research involving human embryonic stem cells; non-hESC SC: stem cell research not involving human embryonic stem cells; Non-SC: research outside stem cell fields. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4: Impact of the Bush hESC policy on U.S. scientists' research direction and productivity of scientists with pre-shock industry affiliations

	(1)	(2)	(3)	(4)	(5)
	All Pubs	SC Pubs	Non-SC Pubs	Non-hESC SC Pubs	hESC Pubs
US Author * T0205	-0.611***	-0.036	-0.509***	-0.046	0.009
	(0.233)	(0.165)	(0.175)	(0.165)	(0.009)
US Author * T0609	-0.343	-0.026	-0.298	-0.033	0.007
	(0.219)	(0.103)	(0.233)	(0.102)	(0.006)
US Author * T1012	-0.037	-0.019	0.007	-0.026	0.007
	(0.245)	(0.094)	(0.283)	(0.094)	(0.007)
Scientist FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	3,800	3,800	3,800	3,800	3,620
Within R^2	0.152	0.142	0.092	0.145	0.003
Scientists	245	245	245	245	245

Notes: All estimates are based on panel OLS regression with year and scientist fixed effects. The dependent variable is the natural logarithm of 1 plus the total number of citation-weighted publications in the relevant research area. Only matched scientists with an industry affiliation in the pre-shock period are included in the analysis. The 1997–2012 period is used for Models 1 through 4. Model 5 limits the window to 1998–2012 for the reasons given in the notes to Table 4. Constant term included in the regression but not reported in the table. Standard errors (in parentheses) are clustered at the scientist level to allow for serial correlation and are robust to arbitrary heteroskedasticity. SC: stem cell research; hESC: stem cell research involving human embryonic stem cells; non-hESC SC: stem cell research not involving human embryonic stem cells; Non-SC: research outside stem cell fields. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: Effect on scientists' citation-weighted publications of acquiring an industry affiliation after the policy change

	(1)	(2)	(4)	(3)	(5)
	All Pubs	SC Pubs	Non-SC Pubs	Non-hESC SC Pubs	hESC Pubs
US Author * T0205	-0.069	-0.092***	0.010	-0.087***	-0.008
	(0.045)	(0.028)	(0.044)	(0.027)	(0.005)
US Author * T0205 * Industry Affiliation	-0.027	0.116	0.210	0.034	0.112**
	(0.373)	(0.257)	(0.411)	(0.254)	(0.057)
US Author * T0609	-0.101**	-0.069**	-0.047	-0.061**	-0.007
	(0.050)	(0.029)	(0.049)	(0.028)	(0.008)
US Author * T0609 * Industry Affiliation	-0.391	0.114	-0.107	0.111	0.017
	(0.374)	(0.241)	(0.416)	(0.233)	(0.053)
US Author * T1012	-0.071	-0.046**	-0.033	-0.039*	-0.009*
	(0.047)	(0.023)	(0.048)	(0.023)	(0.005)
US Author * T1012 * Industry Affiliation	-0.156	0.237	0.047	0.203	0.054*
	(0.358)	(0.240)	(0.394)	(0.238)	(0.030)
T0205 * Industry Affiliation	0.312	-0.506***	0.424	-0.480***	-0.035***
	(0.289)	(0.179)	(0.329)	(0.180)	(0.012)
T0609 * Industry Affiliation	0.252	-0.689***	0.392	-0.724***	0.027
	(0.285)	(0.159)	(0.329)	(0.154)	(0.040)
T1012 * Industry Affiliation	-0.049	-0.732***	0.158	-0.718***	-0.031*
	(0.276)	(0.158)	(0.315)	(0.159)	(0.017)
Industry Affiliation	-0.196	0.554***	-0.240	0.542***	0.015***
	(0.242)	(0.136)	(0.280)	(0.137)	(0.005)
US Author * Industry Affiliation	0.182	-0.108	-0.104	-0.075	-0.030
	(0.319)	(0.218)	(0.355)	(0.215)	(0.022)
Scientist FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	68,025	68,025	68,025	68,025	64,605
Within R^2	0.139	0.082	0.084	0.084	0.003
Scientists	4,374	4,374	4,374	4,374	4,374

Notes: All estimates are based on panel OLS regression with year and scientist fixed effects. Only scientists without an industry affiliation in 2001 and therefore able to acquire a new type of affiliation are included in the sample. The 1997–2012 period is used for Models 1 through 4. Model 5 limits the window to 1998–2012 for reasons explained in footnote to Table 4. Constant term included in the regression but not reported in the table. Standard errors (in parentheses) are clustered at the scientist level to allow for serial correlation and are robust to arbitrary heteroskedasticity. SC: stem cell research; hESC: stem cell research involving human embryonic stem cells; non-hESC SC: stem cell research not involving human embryonic stem cells; Non-SC: research outside stem cell fields. *** p<0.01, ** p<0.05, * p<0.1.

Table A.6: International collaboration results following the Bush policy change excluding control scientists based in European countries

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample			*Matched Sample*		
	Pub Involves hESC Int Flex Collab	Pub Involves non-hESC SC Int Flex Collab	Pub Involves Int Flex Collab	Pub Involves hESC Int Flex Collab	Pub Involves non-hESC SC Int Flex Collab	Pub Involves Int Flex Collab
US Author * Post 2001	0.001***	-0.019*	-0.042**	0.001***	-0.032**	-0.083***
	(0.000)	(0.010)	(0.018)	(0.000)	(0.015)	(0.031)
Scientist FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	Yes	Yes
Time FE	No	No	No	Yes	No	No
Obs.	33,726	33,618	32,812	15,617	15,556	15,150
Within R^2	0.001	0.007	0.030	0.000	0.009	0.032
Scientists	4,722	4,719	4,714	2,692	2,690	2,687

Notes: All estimates are based on panel OLS regression with scientist fixed effects. Sample period from 1998-2009. We include all observations for publications from 2001-2009 in the variable 'Post 2001' due to limited observations for control scientists in Australia, Canada, and New Zealand in more narrow time windows. This also closely tracks when research subject to the Bush Administration's policy would have been published. In 2009, Obama reversed Bush era funding restrictions lowering the need for U.S. scientists to collaborate to acquire resources for hESC research. In this period, we see a reversal in the hESC collaboration results of the main paper, suggesting that it leads scientists to change collaboration behavior and therefore is inappropriate to pool with the results in the period in which collaboration may have been driven by the need for resources. As a result, exclude this period from this robustness test. The dependent variable is only observed if in year *t* scientist *i* has a publication. The period in the analysis is 1998–2012 inclusive. All scientists with an industry affiliation in the pre-shock period are excluded. Models 1 to 3 include a control variable measuring whether a scientist *i* had an industry affiliation in year *t*. Time FEs in Model 4 are 98-01, 02-05, 06-09. Constant term included in the regression but not reported in the table. Standard errors (in parentheses) are clustered at the scientist level to allow for serial correlation and are robust to arbitrary heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1.

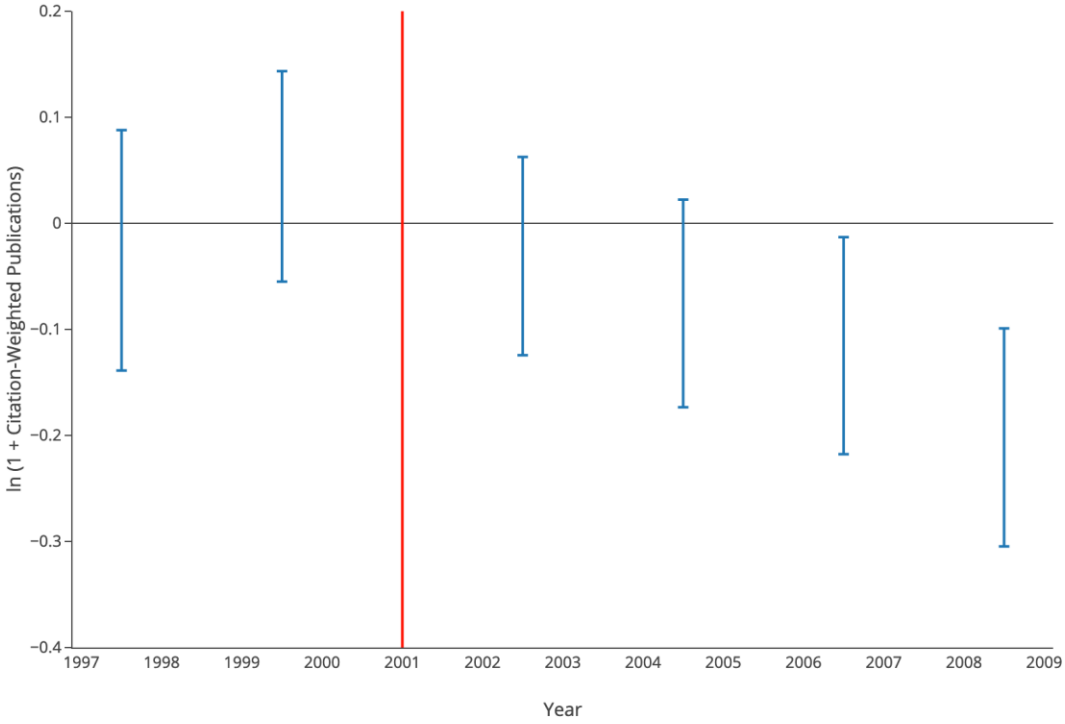
Table A.7: Changes in the collaborative profile of scientists' publications after the policy change by past involvement in embryonic stem cell research

	(1)	(2)	(3)	(4)	(5)	(6)
	Pub Involves hESC Industry Collab	Pub Involves non-hESC SC Industry Collab	Pub Involves Industry Collab	Pub Involves hESC Int Flex Collab	Pub Involves non-hESC SC Int Flex Collab	Pub Involves Int Flex Collab
US Author * T0205	0.000	-0.015***	-0.029**	-0.001	-0.017**	-0.037**
	(0.000)	(0.005)	(0.012)	(0.001)	(0.007)	(0.014)
US Author * T0205* Has ESC Pub 01	0.008*	0.031	0.067	0.009**	0.009	-0.003
	(0.005)	(0.022)	(0.045)	(0.004)	(0.031)	(0.062)
US Author * T0609	0.001	-0.012**	-0.014	-0.001	-0.007	-0.024
	(0.001)	(0.005)	(0.014)	(0.001)	(0.007)	(0.017)
US Author * T0609 * Has ESC Pub 01	0.004	0.011	0.038	0.001	0.001	-0.025
	(0.007)	(0.021)	(0.045)	(0.006)	(0.037)	(0.060)
US Author * T1012	-0.001	-0.012**	-0.033**	-0.003	-0.005	-0.011
	(0.002)	(0.006)	(0.016)	(0.002)	(0.008)	(0.021)
US Author * T1012 * Has ESC Pub 01	-0.013	-0.014	-0.025	-0.033	-0.058	-0.073
	(0.010)	(0.024)	(0.061)	(0.023)	(0.054)	(0.081)
T0205 * Has ESC Pub 01	-0.004	-0.040**	-0.079**	-0.006*	-0.027	0.022
	(0.003)	(0.019)	(0.039)	(0.003)	(0.029)	(0.057)
T0609 * Has ESC Pub 01	0.004	-0.041**	-0.079**	0.001	-0.018	-0.021
	(0.004)	(0.019)	(0.039)	(0.005)	(0.035)	(0.054)
T1012 * Has ESC Pub 01	0.010	-0.017	-0.025	0.032	0.024	0.011
	(0.010)	(0.022)	(0.054)	(0.023)	(0.053)	(0.074)
Scientist FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	29,500	29,347	28,610	29,507	29,398	28,587
Within R^2	0.007	0.005	0.078	0.007	0.002	0.035
Scientists	4,120	4,116	4,108	4,124	4,122	4,117

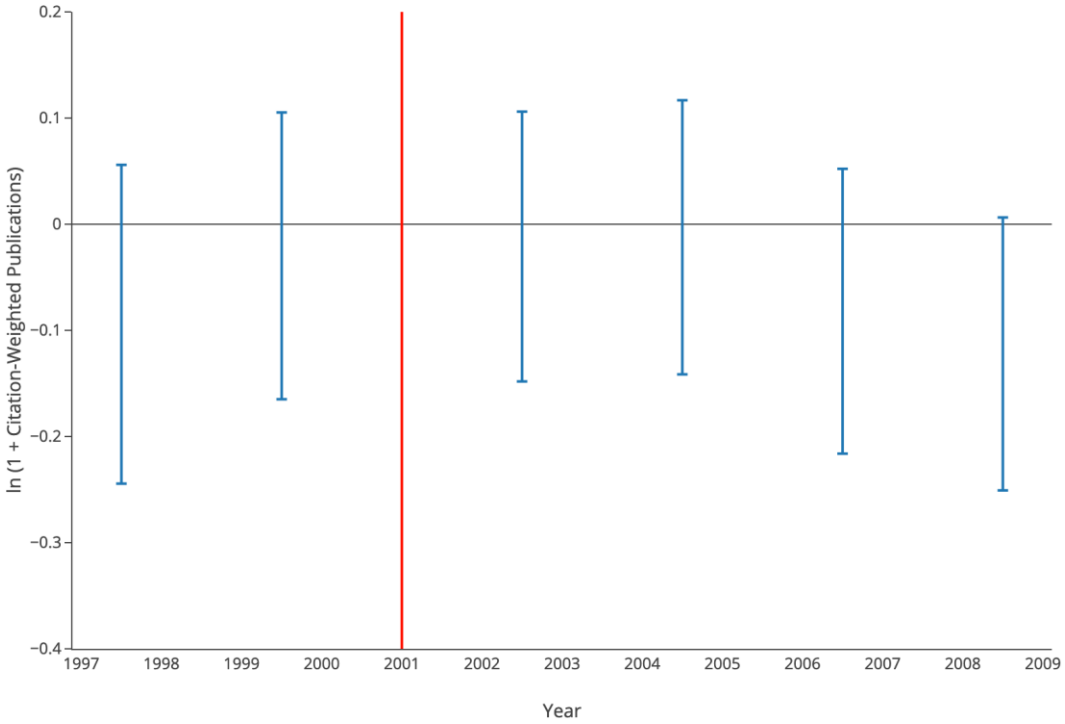
Notes: All estimates are based on panel OLS regression with scientist fixed effects and time period fixed effects for the 2002–2005, 2006–2009, and 2010–2012 periods (with 1998–2001 the omitted time-period dummy variable). The dependent variable is only observed if in year *t* scientist *i* has a publication. The period in the analysis is 1998–2012 inclusive. All scientists with an industry affiliation in the pre-shock period are excluded. Models 1 to 3 include a control variable measuring whether a scientist *i* had an industry affiliation in year *t*. Constant term included in the regression but not reported in the table. Standard errors (in parentheses) are clustered at the scientist level to allow for serial correlation and are robust to arbitrary heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1.

Figure A.1: Impact of the Bush policy on U.S. scientists' non-stem cell research productivity

Panel A: Changes in non-stem cell citation-weighted publications (full sample)



Panel B: Changes in non-stem cell citation-weighted publications (matched sample)



Notes: Figures show the results from Scientist FE models. Years are grouped into two-year periods with the exception of the base year, 2001. Scientists with a pre-shock industry affiliation are excluded from the analysis.

Online Appendix B: Extensions of the Model

B.1: An extension of the model with a generic production function

Agent *i* has to decide to allocate her effort between projects A and B. We can define the agent's production function as follow:

$$f(e_i) = f_A(e_{i,A}) + f_B(e_{i,B})$$

in which

$$f_A(e_{i,A}) = \begin{cases} 0 & if\ e_{i,A} \le \alpha_i \\ \gamma_{i,A} f(e_{i,A} - \alpha_i) & if\ e_{i,A} > \alpha_i \end{cases}$$

and, similarly,

$$f_B(e_{i,B}) = \begin{cases} 0 & if\ e_{i,B} \le \beta_i \\ \gamma_{i,B} f(e_{i,B} - \beta_i) & if\ e_{i,B} > \beta_i \end{cases}$$

The production function $f(e)$ is increasing in effort e (i.e., $\frac{\partial f(e)}{\partial e} > 0$) with diminishing returns (i.e., $\frac{\partial^2 f(e)}{\partial e^2} < 0$). The agent solves the following maximization problem:

$$\underset{wrt\ e_{i,A}, e_{i,B}}{\text{maximize}}\ f_A(e_{i,A}) + f_B(e_{i,B})$$

$$\text{subject to } 0 \le \alpha_i, \beta_i, e_{i,A}, e_{i,B} \le 1;\ 0 < \gamma_{i,A}, \gamma_{i,B};\ \text{and } e_{i,A} + e_{i,B} = 1$$

For all inner solutions, Taking the first derivative and solving for $e_{i,A}$, we have:

$$\gamma_{i,A} \frac{\partial f(e_{i,A} - \alpha_i)}{\partial e_{i,A}} - \gamma_{i,B} \frac{\partial f(1 - e_{i,A} - \beta_i)}{\partial e_{i,A}} = 0$$

Let us define $g(e) = \frac{\partial f(e)}{\partial e}$ and its inverse as g^{-1}. Because $\frac{\partial f(e)}{\partial e} > 0$, both $g(e)$ and its inverse g^{-1}, are also positive. We then have:

$$\gamma_{i,A} g(e_{i,A}{}^* - \alpha_i) - \gamma_{i,B}(1 - e_{i,A}{}^* - \beta_i) = 0$$

$$(e_{i,A}{}^* - \alpha_i) g^{-1}(\gamma_{i,A}) - (1 - e_{i,A}{}^* - \beta_i).\, g^{-1}(\gamma_{i,B}) = 0$$

$$e_{i,A}{}^* = \frac{\alpha_i g^{-1}(\gamma_{i,A}) + (1 - \beta_i) g^{-1}(\gamma_{i,B})}{g^{-1}(\gamma_{i,A}) + g^{-1}(\gamma_{i,B})}$$

Taking the derivative of $e_{i,A}{}^*$ with respect to α_i and β_i yields:

$$\frac{\partial e_{i,A}{}^*}{\partial \alpha_i} = \frac{g^{-1}(\gamma_{i,A})}{g^{-1}(\gamma_{i,A}) + g^{-1}(\gamma_{i,B})} > 0$$

$$\frac{\partial e_{i,A}{}^*}{\partial \beta_i} = \frac{-g^{-1}(\gamma_{i,B})}{g^{-1}(\gamma_{i,A}) + g^{-1}(\gamma_{i,B})} < 0$$

Note that the inner solution is the dominant choice only if

$$\gamma_{i,A} f(e_{i,A}{}^* - \alpha_i) + \gamma_{i,B} f(1 - e_{i,A}{}^* - \beta_i) \ge \gamma_{i,A} f(1 - \alpha_i)$$

and

$$\gamma_{i,A} f(e_{i,A}{}^* - \alpha_i) + \gamma_{i,B} f(1 - e_{i,A}{}^* - \beta_i) \ge \gamma_{i,B} f(1 - \beta_i)$$

B.2: An extension of the model with complementary projects

Agent *i* has to decide to allocate her effort between projects A and B. When the projects are full complements, we can define the agent's production function as follow:

$$f(e_i) = f_A(e_{i,A}).f_B(e_{i,B})$$

in which

$$f_A(e_{i,A}) = \begin{cases} 0 & if\ e_{i,A} \leq \alpha_i \\ \gamma_{i,A}\sqrt{e_{i,A} - \alpha_i} & if\ e_{i,A} > \alpha_i \end{cases}$$

and, similarly,

$$f_B(e_{i,B}) = \begin{cases} 0 & if\ e_{i,B} \leq \beta_i \\ \gamma_{i,B}\sqrt{e_{i,B} - \beta_i} & if\ e_{i,B} > \beta_i \end{cases}$$

The agent solves the following maximization problem:

$$\underset{wrt\ e_{i,A}, e_{i,B}}{\text{maximize}}\ f_A(e_{i,A}).f_B(e_{i,B})$$

$$\text{subject to } 0 \leq \alpha_i, \beta_i, e_{i,A}, e_{i,B} \leq 1;\ 0 < \gamma_{i,A}, \gamma_{i,B};\ \text{and } e_{i,A} + e_{i,B} = 1$$

As long as $\alpha_i + \beta_i < 1$, the optimization problem has only one inner solution that involves investing in both projects. Taking the first derivative with respect to $e_{i,A}$ and solving for the optimal amount of effort, we have:

$$\frac{\partial(\gamma_{i,A}.\gamma_{i,B}\sqrt{{e_{i,A}}^* - \alpha_i}\sqrt{1 - {e_{i,A}}^* - \beta_i})}{\partial e_{i,A}} = 0$$

$$\frac{\gamma_{i,A}.\gamma_{i,B}(1 - 2{e_{i,A}}^* + \alpha_i - \beta_i)}{2\sqrt{{e_{i,A}}^* - \alpha_i}\sqrt{1 - {e_{i,A}}^* - \beta_i)}} = 0$$

$${e_{i,A}}^* = 0.5(1 + \alpha_i - \beta_i)$$

Taking the derivatives with respects to α_i and β_i, we have:

$$\frac{\partial {e_{i,A}}^*}{\partial \alpha_i} = 0.5$$

$$\frac{\partial {e_{i,A}}^*}{\partial \beta_i} = -0.5$$

The results suggest that when the two projects are complementary, the predictions of the model always hold.

B.4 Large changes in cost of securing resources for each project can push the agents to invest fully in the other project

For an agent whose optimal solution involves investing in both projects, we should have

$$\sqrt{\frac{\alpha_i}{1-(\alpha_i+\beta_i)}} < \gamma_i < \sqrt{\frac{1-(\alpha_i+\beta_i)}{\beta_i}}$$

Taking the derivative of the lower bound with respect to α_i, we have:

$$\frac{\partial\sqrt{\frac{\alpha_i}{1-(\alpha_i+\beta_i)}}}{\partial\alpha_i} = \frac{1-\beta_i}{\sqrt{\alpha_i(1-(\alpha_i+\beta_i))}} > 0$$

Large increases in α_i can push the lower bound to become larger than γ_i. Note that at extreme, if α_i approaches $1-\beta_i$, the lower bound approaches infinity. As an inner solution becomes infeasible, the agent will optimally invest all her efforts in project B given that γ_i would become smaller than $\sqrt{\frac{1-\beta_i}{1-\alpha_i}}$ for large enough increases in α_i. For large enough increases in β_i, we will have the opposite situation where $\sqrt{\frac{1-(\alpha_i+\beta_i)}{\beta_i}}$ becomes smaller than γ_i and therefore the agent optimally switches to investing all her efforts in project A.

B.4 Change in output with respect to changes in the costs of securing resources

Taking the derivative of ${e_{i,A}}^*$ with respect to α_i and β_i yields:

$$\frac{\partial {e_{i,A}}^*}{\partial\alpha_i} = \frac{1}{{\gamma_i}^2+1} > 0$$

$$\frac{\partial {e_{i,A}}^*}{\partial\beta_i} = -\frac{{\gamma_i}^2}{{\gamma_i}^2+1} > 0$$

Given that ${e_{i,B}}^* = 1-{e_{i,A}}^*$, the derivates have the opposite sign for ${e_{i,B}}^*$. The results suggest that an increase in the cost of securing inputs for project A (i.e., α_i) can lead to an increase in the share of agent's effort invested in project A. Conversely, a decrease in α_i depresses the share of the agent's effort allocated to project A. Plugging in the optimal effort allocation into the production function and taking the derivates with respect to α_i and β_i yield:

$$\frac{\partial f_A({e_{i,A}}^*)}{\partial\alpha_i} = \frac{\partial f_A({e_{i,A}}^*)}{\partial\beta_i} < 0$$

$$\frac{\partial f_B({e_{i,B}}^*)}{\partial\alpha_i} = \frac{\partial f_B({e_{i,B}}^*)}{\partial\beta_i} < 0$$

$$\frac{\partial f(e_i^*)}{\partial \alpha_i} = \frac{\partial f(e_i^*)}{\partial \beta_i} = \frac{-\sqrt{\gamma_i{}^2 + 1}}{2\sqrt{1-(\alpha_i+\beta_i)}} < 0$$

The results suggest that increasing the costs of securing inputs for either project reduces the total output by the same amount.

B.5 A decline in α_i or β_i cannot shift the agent from an inner solution to a corner solution

For an agent whose optimal solution involves investing in both projects, we should have

$$\sqrt{\frac{\alpha_i}{1-(\alpha_i+\beta_i)}} < \gamma_i < \sqrt{\frac{1-(\alpha_i+\beta_i)}{\beta_i}}$$

Note that any decline in α_i or β_i decreases the lower bound and increases the upper bound on this inequality, because:

$$\frac{\partial \sqrt{\frac{\alpha_i}{1-(\alpha_i+\beta_i)}}}{\partial \alpha_i} = \frac{1-\beta_i}{\sqrt{\alpha_i(1-(\alpha_i+\beta_i))}} > 0$$

$$\frac{\partial \sqrt{\frac{\alpha_i}{1-(\alpha_i+\beta_i)}}}{\partial \beta_i} = \frac{\alpha_i}{\sqrt{\alpha_i(1-(\alpha_i+\beta_i))}} > 0$$

$$\frac{\partial \sqrt{\frac{1-(\alpha_i+\beta_i)_i}{\beta_i}}}{\partial \alpha_i} = \frac{-1}{2\sqrt{\beta_i(1-(\alpha_i+\beta_i))}} < 0$$

$$\frac{\partial \sqrt{\frac{1-(\alpha_i+\beta_i)_i}{\beta_i}}}{\partial \beta_i} = \frac{\alpha_i - 1}{2\sqrt{\beta_i(1-(\alpha_i+\beta_i))}} < 0$$

Therefore, γ_i would still satisfy the necessary condition for an inner solution to exist after any decline in α_i or β_i.

B.6 Model with endogenous costs of securing resources

We define the production model as before:

$$f(e_i) = f_A(e_{i,A}) + f_B(e_{i,B})$$

in which

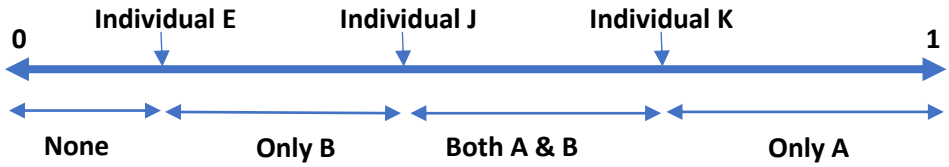
$$f_A(e_{i,A}) = \begin{cases} 0 & if\ e_{i,A} \leq \alpha_i \\ \gamma_{i,A}\sqrt{e_{i,A} - \alpha_i} & if\ e_{i,A} > \alpha_i \end{cases}$$

and,

$$f_B(e_{i,B}) = \begin{cases} 0 & if\ e_{i,B} \leq \beta_i \\ \gamma_{i,B}\sqrt{e_{i,B} - \beta_i} & if\ e_{i,B} > \beta_i \end{cases}$$

However, in this case, α_i and β_i, are both endogenous to the number of people who has invested in each project. To establish the sorting of individuals into projects, we need to have a sorting of ability among individuals. Let's assume a spectrum of individuals with a uniform distribution of ability from 0 to 1. An individual with a higher level of ability would face lower levels of α_i and β_i, everything else equal.

We assume that the baseline expectation of return to invested effort in project A is higher than that in project B. Therefore, ceteris paribus, more capable individuals have a preference for working on project A than project B. the figure below shows the distribution of individuals between the two projects in an equilibrium in which some individuals work on both projects at the same time.



We have the following distribution of individuals across the four possibilities:

- 1-I: The proportion of individuals who only invest in project A
- I-J: the proportion of individuals who invest in both projects
- J-E: the proportion of individuals who only invest in project B
- E: the proportion of individuals who invest in neither project

For each individual, we define α_i and β_i as follow:

$$\alpha_i = \frac{\alpha(1-J)}{i}\ and\ \beta_i = \frac{\beta(K-E)}{i}$$

i indicates the individual's ability (between 0 and 1). α and β indicate the baseline costs of securing resources for project A and B are exogenously set. $(1-J)$ is the proportion of individuals invested in project A and $(K-E)$ is the proportion of individuals invested in project B. Note that the individual cost of securing resources for each project is positively correlated with the number of individuals bidding for these resources and negatively correlated with the ability of the individual.

Let us also assume that $\gamma_{i,A} = i.\gamma$ and $\gamma_{i,B} = i$, where $\gamma > 1$ is the maximum possible relative expected return to a unit of effort invested in project A versus project B. We assume that the expected return to investment in each project does not depend on the number of individuals investing in that project. In our empirical context, the expected return to investment in any area of stem cell research is determined by the total number of scientists active at the global level. Therefore, partial changes in the number of U.S. scientists invested in each area should not materially change the expected return to investment in that area.

In equilibrium, individual E (in the figure above) should be indifferent between investing in project B or staying out; individual J should be indifferent between investing in project B or investing in both projects; and individual I should be indifferent between investing in both projects and investing only in project A. Formally, we have

For individual K:

$$K\gamma\sqrt{1-\alpha_I} = K\sqrt{(1+\gamma^2)(1-\alpha_K-\beta_K)}$$

$$\Rightarrow \gamma\sqrt{1-\frac{\alpha(1-J)}{K}} = \sqrt{(1+\gamma^2)\left(1-\frac{\alpha(1-J)}{K}-\frac{\beta(K-E)}{K}\right)}$$

For individual J:

$$J\sqrt{1-\beta_J} = J\sqrt{(1+\gamma^2)\left(1-\alpha_J-\beta_J\right)}$$

$$\Rightarrow \sqrt{1-\frac{\alpha(1-J)}{J}} = \sqrt{(1+\gamma^2)\left(1-\frac{\alpha(1-J)}{J}-\frac{\beta(K-E)}{J}\right)}$$

And, for individual E:

$$E\sqrt{1-\beta_E} = 0$$

$$\Rightarrow E\sqrt{1-\frac{\beta(K-E)}{E}} = 0$$

Solving this system of equations yields:

$$E = \frac{\beta K}{1+\beta}$$

$$K = \frac{\alpha(1+\beta)\gamma^2}{\alpha\beta(1+\gamma^2-\gamma^4)+\alpha\gamma^2+\gamma^2(1-\beta\gamma^2)}$$

$$J = \frac{\alpha\beta(1+\gamma^2-\gamma^4)+\alpha\gamma^2}{\alpha\beta(1+\gamma^2-\gamma^4)+\alpha\gamma^2+\gamma^2(1-\beta\gamma^2)}$$

Note that for $\gamma > 1$ we have $K > J$. Also, for $\gamma < \sqrt{\frac{1}{b}}$, both K and J will be positive.

The total amount of optimal effort spent on project A across all individuals is equal to:

$$E_A^* = (1-K) + \int_J^K e_{i,A}^* di$$

$$E_A^* = (1-K) + \int_J^K \frac{\gamma^2(1-\beta_i)+\alpha_i}{\gamma^2+1} di$$

$$E_A^* = (1-K) + \int_J^K \frac{\gamma^2(1-\beta_i)+\alpha_i}{\gamma^2+1} di$$

$$E_A^* = (1-K) + \int_J^K \frac{\gamma^2(1-\beta_i)+\alpha_i}{\gamma^2+1} di$$

$$E_A^* = (1-K) + \int_J^K \frac{\gamma^2\left(1-\frac{\beta(K-E)}{i}\right)+\frac{\alpha(1-J)}{i}}{\gamma^2+1} di$$

$$E_A^* = (1-K) + \frac{\alpha(1-J)(1+\beta)\log i + \gamma^2(1+\beta)i - \gamma^2\beta K\log((1+\beta)i)}{(\gamma^2+1)(1+\beta)}\Bigg]_J^K$$

$$E_A^* = (1-K) + \frac{(\alpha(1-J)(1+\beta)-\gamma^2\beta K)\log\frac{K}{J}}{(\gamma^2+1)(1+\beta)} + \frac{\gamma^2}{\gamma^2+1}(K-J)$$

External actors (i.e., policymakers and firms' managers) can influence individuals' allocation of effort and their distribution across the projects by targeting the base value α and β. Below, we evaluate the effect of a change in α on E_A^*.

$$\frac{\partial E_A^*}{\partial\alpha} = \frac{(1-J)}{(\gamma^2+1)}\log\frac{K}{J} - \frac{1}{\gamma^2+1}\frac{\partial K}{\partial\alpha} - \frac{\gamma^2}{\gamma^2+1}\frac{\partial J}{\partial\alpha} + \frac{(\alpha(1-J)(1+\beta)-\gamma^2\beta K)}{(\gamma^2+1)(1+\beta)}\frac{\partial(log\frac{K}{J})}{\partial\alpha}$$

We can show that $\frac{(\alpha(1-J)(1+\beta)-\gamma^2\beta K)}{(\gamma^2+1)(1+\beta)}\frac{\partial(log\frac{K}{J})}{\partial\alpha}=0$. Therefore:

$$\frac{\partial E_A^*}{\partial\alpha}=\frac{(1-J)}{(\gamma^2+1)}\log\frac{K}{J}-\frac{1}{\gamma^2+1}\frac{\partial K}{\partial\alpha}-\frac{\gamma^2}{\gamma^2+1}\frac{\partial J}{\partial\alpha}$$

We have:

$$\frac{\partial K}{\partial\alpha}=\frac{\gamma^4(1+\beta)(1-\beta\gamma^2)}{(\alpha\beta(1+\gamma^2-\gamma^4)+\alpha\gamma^2+\gamma^2(1-\beta\gamma^2))^2}$$

$$\frac{\partial J}{\partial\alpha}=\frac{\gamma^2(1-\beta\gamma^2)(\beta(1+\gamma^2-\gamma^4)+\gamma^2)}{(\alpha\beta(1+\gamma^2-\gamma^4)+\alpha\gamma^2+\gamma^2(1-\beta\gamma^2))^2}$$

Which leads to:

$$\frac{\partial E_A^*}{\partial\alpha}=\frac{(1-J)}{(\gamma^2+1)}\log\frac{K}{J}+\frac{\gamma^4(\beta\gamma^2-1)(1+\beta+\gamma^2+\beta(1+\gamma^2-\gamma^4))}{(\alpha\beta(1+\gamma^2-\gamma^4)+\alpha\gamma^2+\gamma^2(1-\beta\gamma^2))^2}$$

We can show that for $\gamma<\sqrt{\frac{1}{b}}$ (which is the criteria for the above equilibrium to exist), we will have $\frac{\partial E_A^*}{\partial\alpha}>0$. In other words, any marginal increase in the baseline cost of acquiring resources for project A (imposed by policymakers or firms' managers) would lead to an increase in the total aggregated effort invested in project A at the expense of a decline in the total aggregated effort invested in B.