**Organized Learning:**
**The Case of Scientists Working in a Mission Agency**

The dominant theme in a recent review of the organizational learning paradigm (Argote and Miron-Sepktor, 2011) is the accumulation of experience leads to knowledge. This perspective becomes particularly interesting in the context of basic and applied research, which is where one could argue that learning is organized or “mindful” to use the term of Argote and Miron-Spektor, 2011 because it is the objective of the organization. While there are a number of studies of product development Brown and Eisenhardt, 1995) in the industrial and service sectors, to our knowledge there are none of scientific research in the public sector, especially in mission agencies that in many ways are designed to produce new services for the public. Scientific research is of course a special kind of learning from experience and the issue is what kinds of organizational practices encourage this. This context provides an opportunity to advance the theory of organizational learning.

Learning at the individual level can be measured by various kinds of cognitive approaches such as a scale on the effectiveness of learning or by reductions in the number of modifications made in software products. At the organizational level, innovation represents an important way of describing the products of learning, as for example changes in the characteristics of the products or services provided (Argote and Miron-Sepktor, 2011; (Boh, et al., 2007; Hage and Meeus, 2006) or more directly by changes in the strategy and tactics of NGOs attempting to change the behavior of pregnant women (Valadez et al., 2005). Still a third way is to measure the presence of learning mechanisms appropriate for scientists such as critical thought, cross-fertilization of technical ideas, and two patterns of communication about research projects. In this way, one can separate measures of learning from the effects of learning as indicated in improved performances such as productivity or innovation or in the study of scientific research from papers and patents. These latter measures are not relevant for the most part in this applied research agency concerned more with ensuring the accuracy of information obtained from satellites and where the output measures differ considerably across the three divisions. Therefore, the focus on four kinds of learning mechanisms appears to be a more appropriate kind of learning measure.

The objective of this paper is to build upon the framework of McGrath and colleagues (Arrow et al., 2000, McGrath and Argote, 2001) as cited in Argote and Miron-Sepktor, 2011: 1125) and explore its usefulness in tthe Center for Satellite Applications and Research (hereafter STAR), a part of the National Oceanographic and Atmospheric Agency (hereafter NOAA). A great deal of NOAA’s work in climate and weather analysis relies on the use of remote sensing (satellite) data, and STAR is responsible for the development of satellite instruments and of algorithms that translate data from satellites into formats and products that can be used by NOAA analysts and any interested parties around the world, most particularly weather forecasters and academics in oceanography and atmospheric research. For example, STAR has developed products for measuring the thickness of arctic sea ice, predicting harmful algal blooms in the Chesapeake Bay, and detecting wild forest fires, among many others (Powell, Ohring, Kalb, et al., n.d). In this respect, STAR is typical of the many kinds of research centers in public research organizations that remain largely invisible but develop public use data and original research.

In the recent review cited above, Argote and Miron-Sepktor (2011) emphasizes the importance of members, tools, tasks and networks connecting members and tools. We build upon this framework by examining the impact on learning of: (1) three ways of describing research tasks, (2) several kinds of networks and (3) several characteristics of the research staff or members. The impact on learning is examined for each of the four mechanisms described above as well as an index constructed from these components. The first section discusses the theoretical framework of tasks, collaborative networks, and members and the specific hypotheses that are tested while the second section considers the methods used to collect the data for this testing. The third section reports the support for the hypotheses for both mechanisms of learning as well as their combination in an index of learning while the fourth section reports a multivariate analysis of the impact of these different ways of describing how research is organized.

## Theoretical Framework

Scientific research is organized learning where one attempts to accelerate the accumulation of experience and its conversion into knowledge. It is not, of course, the only kind. Another important type is quality-work circles where workers attempt to solve problems associated with productivity (Nonaka and Takeuchi, 1995). Another type is product-development teams, which have been extensively studied as well (Brown and Eisenhardt, 1995; Keller, 2001). But scientific research stands apart as a more interesting form of “mindful” learning since it is precisely concerned with the production of knowledge including knowledge that does not have any necessary immediate commercial benefit as in this specific case. Some of the free products that STAR provides give commercial benefits to other organizations such as local weather forecasters. However, the majority of the products are for the benefit of weather forecasters and geophysicists attempting to understand climate and climate change.

Focusing on the learning of knowledge workers is a particularly important extension of the organizational learning model. Although the occupational literature has observed a gradual movement recently towards an appreciation of knowledge workers (Crech, Rubineau, Selby and Seron, 2011; Gorman and Sandefur, 2011; Sandefur, 2009), applied scientists have been largely ignored. A particular important reason for studying how knowledge workers learn in general and scientists, whether basic or applied in particular, is because they are perceived to be an essential ingredient in post-industrial society (Bell, 1973) and are certainly an important part of what some have called the creative class (Florida, 2004).

The starting point for the development of ideas about how factors might impact on the amount of learning that occurs in applied research work is to consider the kinds of tasks. In this context, it is important to make a distinction between two kinds of tasks in scientific research because of the special nature of STAR. While the bulk of its research is applied, at the same time some researchers at STAR are to a certain extent and especially in the three cooperation branches that are part of one division focused on basic research about satellites or about the atmosphere and the ocean and their interactions. Our first set of hypotheses examines what might be called general research tasks and more specifically what percent of the time in spent in each kind of activity. In contrast, the second set of research tasks focused on applied tasks found only in STAR. Finally, still a third way of describing the research tasks for both basic and applied research is the relative emphasis on various processes that lead to innovation.

As important as it is to identify tasks, networks, and member characteristics that facilitate the learning mechanisms as we have defined them, the reverse is equally important. How do tasks in particular *prevent* learning? That is, by far, the more provocative question, which highlights what is usually missing in studies of organizational learning. Can we identify those organizational practices that would appear to be diminish learning.

### Basic Scientific Research Tasks

One might make the assumption that all research results in some kind of learning even if it is only learning what kind of experimental manipulation does not work, but this ignores the fact that a lot of research work is routine, in which little actual learning occurs. What is needed is a list of research tasks and in particular ones that can be applied across a wide range of disciplines and in both the public and private sectors. The specific research activities that we studied in STAR, common to all kinds of research, including new product development, are the percent of time spent in:

- Routine technical tasks;
- Fundamental understanding;
- Planning, reviewing papers, and documentation;
- Administration and organizational paper work;
- Organizational training and public relations.

These five sets of tasks, each of which can be further delineated, indicate how complex is the job of a scientist. The essential distinction between the third and the fourth activity on this list is between professional tasks associated with scientific research and bureaucratic responsibilities because the research is conducted in an organization, in this instance a public research laboratory with a mission. A recent study (Hage, et al., 2012) found a similar set of tasks useful for describing the differences between six major scientific areas of research--biology, chemistry, geosciences, alternative energy, material sciences, and interdisciplinary areas. As necessary as routine work, planning and review, and administration are, these research tasks are much less likely than work addressing fundamental understanding to lead to learning. This is not to say that over time as one gains experience doing each of these tasks, there might not be gains in the speed or effectiveness with which they are accomplished, two other ways of discussing learning, but they are not likely to be associated with the learning mechanisms that we have described above because they are less likely to lead to the creation of the kinds of knowledge that are the objectives of this mission agency. Given this list, our hypothesis is:

*1a. The greater the amount of time spent on research with the objective of fundamental understanding, the greater the amount of learning.*

Since we suggested above that it is important to identify when learning for the purposes of knowledge creation does *not* occur, we could add another four hypotheses representing the lack of learning. But most of these are likely to be non-significant and for several reasons. However, one activity in which higher allocations of effort might be expected to lead to less learning is the amount of time spent on organizational tasks such as managing contractors (an important task in STAR) and paper work not related to research. Thus, a second hypothesis:

*1b. The greater the amount of time spent on organizational tasks, the less the amount of learning.*

**Applied Scientific Research Tasks**

Above, we suggested that STAR was concerned with both basic and applied knowledge creation. This poses the question of what are some of the specific kinds of knowledge that this research unit should be trying to develop. This is an important point in developing a framework for organized learning. To describe research only in general terms misses the specifics of knowledge creation appropriate for a specific discipline and/or research organization. Each of the major disciplinary areas listed above has specific kinds of intellectual problems that have to be solved, i.e. fundamental understanding comes in different shapes and sizes. And just as we would expect that not all general research tasks lead to learning we also hypothesize that some intellectual problems within a specific disciplinary area/organizational context are not only more interesting than others but are more likely to be "better teachers". For the geosciences in STAR, the following list describes the range of problems that these scientists are attempting to solve:

- Locating the causes of errors in data;
- Developing new algorithms;
- Reviewing the designs of sensors;
- Analyzing predictive models.

In this instance, we hypothesize that two of these tasks are more likely to result in learning because they are more closely connected to the specific aims of the geophysicists who work in STAR, that is providing new algorithms for the benefit of the country, e.g. an early warning system for coral reef bleaching, and better predictions of the tracks of hurricanes. Hence, the following hypotheses:

*2a. The greater the amount of time spent developing new algorithms, the greater the amount of learning;*

*2b. The greater the amount of time spent analyzing predictive models, the greater the amount of learning.*

Locating the causes of errors and also considering how best to design sensors for capturing data reflect quite different ways of accumulating experience but they are less likely to lead to knowledge creation as quickly as the other two tasks.

**Innovative Research Process Tasks**

Research processes reflect the interconnection between how the research is conducted and the influence of the organizational context. In this study, three important kinds of research processes are explored: challenge, creativity, and risk-taking. The latter two have long been associated with firms that are more innovative. The central argument is that if managers encourage individuals to be more creative, such as setting aside free time for this, and also encourage risk-taking, will this lead to more innovation via the process of learning. In particular, freedom to explore new ideas and being able to take risks are graduations specifically adapted to the scientific research and risk-taking is a key idea in the literature on innovation (Hage, 2011; Sicotte and Langely, 2000). But while challenge has not received the same attention in the literature on innovation as creativity and freedom to explore new ideas, it is quite similar in that the assumption is that the greater the challenge of the scientific problem the greater the opportunities for learning. Argote and Miron-Sepktor (2011) mention two of these important research processes as part of the context of learning: risk-taking and creativity. Those of high status and power tend to ignore the ideas of those beneath them in rank while lower ranking individuals are less likely to take risks (Bunderson and Reagans, 2011). When managers encourage risk-taking, then scientists are more likely to learn. Argote and Miron-Sepktor (2011) also note the importance of connecting studies of creativity or knowledge creation to the study of learning. These three kinds of research processes all have the same essential argument namely the more that scientists are encouraged to be creative and to explore new ideas and accept challenging problems, all ways of describing taking risks, the more likely they are to learn. Three hypotheses that can be generated from this argument are:

*3a. The greater the amount of time spent working on challenging problems, the greater the amount of learning;*

*3b. The greater the amount of time spent on being creative, the greater the amount of learning.*

*3c. The greater the amount of time spent on exploring new ideas, the greater the amount of learning.*

These three research processes also relate to another literature, namely that on job satisfaction from intrinsic rewards (Johnson, Mortimer, Lee, et al., 2007). One can easily imagine how rewarding scientists who work in public research laboratories would find these kinds of research processes. They go to the heart of what it means to be a scientist.

Closely related to the above research processes is the question of the autonomy of scientists in pursuing research. Scientists will learn more when they have authority to make decisions about their research. Thus, this hypothesis:

*4. The greater the autonomy of researchers the greater the amount of learning.*

**Research Networks and Collaborations**

An important and common characteristic of research is that it usually involves working with others (Hand 2010). Just as we have three dimensions for describing research processes, there are three ways of characterizing the nature of working with others: working in teams, networks across teams, and external networks. Research teams are much like quality work circles, a way of encouraging individuals to work together to solve problems. Of course, the relative importance of status and power may interfere with how effective teams are for learning. External networks in the context of STAR means working not only with other units of NOAA but also with the National Aeronautical and Space Administration, the U.S. Navy, Lockheed Martin, etc. In various ways, each of these measures builds upon a fundamental finding in the research literature on innovation, namely that diversity is more likely to lead to innovation. Here the issue is the sheer diversity of members is likely to increase learning, the prior step before innovation. The specific hypotheses are:

*5a. The greater the amount of time spent in teamwork both in the project and in other projects, the great the amount of learning;*

*5b. The greater the amount of time spent in external networks, the greater the amount of learning.*

Just as the three processes of research relate to another literature, namely that on job satisfaction because they represent intrinsic rewards, the three measures also refer to another part of this same literature, namely what is called new work practices, that is the tendency for each of these to become more common in all kinds of organizations (Homan, Wall, Clegg, et al. 2003; Kalleberg, Marsden, Reynolds, et al. 2006) but these have not been related to the amount of learning that occurs.

The Quality and Diversity of the Technical Staff

An aspect of research as organized learning that is frequently ignored is that there is an array of equipment that has to be kept in good working order for experiments to be conducted. In some respects, NOAA represents an extreme of this because not only are there a number of different satellites but planes, ships, radar stations, weather stations, etc. are collecting enormous amounts of data around the world. And while STAR is primarily concerned with the signals from satellites, these require a considerable amount of technical back-up as well. Given this line of reasoning then the argument would be that the quality and the diversity of technical staff should also impact on the ability of scientists to learn as well. We offer two hypotheses for testing this line of reasoning:

*6a. The greater the amount of high quality technical staff, the greater the amount of learning;*

*6b. The better the mix of the staff, the greater the amount of learning.*

In summary, the more that work concentrates on what might be called basic research, emphasizes challenge, creative and high risk processes, and is completed in collaborative networks, with competent staff and that researchers have authority to make decisions about their research the more learning is likely to occur.

## Methods

The primary data used in this study come from a survey designed specifically for research organizations and scientists. The survey was developed through an extensive literature review with input from 15 focus groups that included bench scientists, engineers and technologists, as well as their managers, across various R&D tasks, and it has been field-tested in a number of research organizations (Jordan and Streit 2003; Jordan et al. 2003; Jordan 2005). In total, the survey encompasses 42 job attributes that were identified as critical for creating an environment that fosters excellent research. In this paper, we explore only those items related specifically to how learning is organized.

The data on STAR were collected in three waves, each two years apart 2005 2007, and 2009. The response rates were respectively 79 (n = 58), 56 (n = 44), and 50 percent (n = 31). All scientists working at STAR were invited to participate. The decline in the number of scientists reflects the impact of retirements and the gradual movement of more and more work into contracts with private contractors. It is more difficult to explain the declining response rate.

After entry into a computer, the data were edited and corrected. A small number of incomplete questionnaires were completed with an iterative regression procedure {Raghunathan, 2001 #1731}. This, and the statistical analyses, were done with R software {R Core Team, 2012 #2995}.

**The Measurement of Learning**

In the introduction, we suggested that learning at the individual level can be separated from the effects of learning as measured by increased productivity or innovation, changes in product characteristics or in strategies and tactics (Boh, et al., 2007; Valadez, et al. 2005). This approach focuses on the mechanisms or ways in which scientists learn. In this research, we use two mechanisms of learning and two measures of communication: critical thought and cross-fertilization, and good communication among researchers on projects and between researchers and management about their projects. While this represents a cognitive approach, it does allow us to separate the way in which learning occurs from its consequences. As we have already suggested, the specific kinds of outputs such as new algorithms or reduction in errors or papers vary in importance across the branches within the divisions (a total of nine) and occur with different frequency, making the measure of the consequences of learning difficult in this study.

Cross-fertilization of ideas is an obvious way of learning for scientists but less obvious is the importance of critical thought. Too much emphasis has been placed on having good ideas and not enough on how to separate what part of a good idea is actually bad and needs to be rectified. This is the task of critical thought. Good communication facilitates the exchange of ideas and supports critical thought.

For each mechanism of learning, the scientists were asked to report what percent of the time, it was true among five categories: 0 to 20%, 21 to 40%, 41 to 60%, 61 to 80%, and 81% to 100%. The means for each wave are reported in Table One, where 3 represents 41 to 60% of the time. Critical thought increased from 3.67 in 2005 to 4.07 in 2007 but then declined to 3.58 in 2009 while cross-fertilization also increased slightly from 3.05 to 3.38. Communication on projects increased in each panel and communication with management increased from 2005 to 2007. Combining these, the index of learning increased from 2005 to 2007 and again to 2009. Given the small sample size, however, these differences are not statistically significant. The index of learning represents the combination of the responses to the four questions, which are first standardized then added together, and then the index is rescaled to range from 1 to 5 to make it comparable to the constituent items. Cronbach's alpha for the index is 0.80.

Despite this high level of internal consistency, in the first phase of the analysis, we report zero-order correlations between the attributes describing how research is organized and its impact on each component of the learning index as well as the learning index. The analysis provides some insights into when critical thought is maximized as distinct from cross-fertilization, which is the more commonly reported mechanism of learning. It should be emphasized that we are not measuring organizational learning but instead the learning of individual scientists in what might be called an organization dedicated to learning.

**The Measurement of the Ways in Which Research is Organized**

A first question about the way in which research is organized asks scientists to report what percentage of the time they allocate to each of five kinds of basic research tasks: routine tasks, research for fundamental understanding, professional tasks, organizational tasks, and training, public relationships and other outreach categories. This was followed by a second question asking for the time allocated to research for fundamental understanding, what percent is involved each of following applied objectives: causes of errors, new algorithms, designs of sensors, and analyzing predictive weather models. All of these objectives are part of STAR's mission within NOAA.

The questions about research processes and collaborative networks were framed in the same way as the two questions about learning. The same five-point scale representing what percentage of the time of a particular attribute is present was used to measure the extent of the emphasis on creativity, teamwork, etc.

Since the extent of learning is constructed with four questions, we also constructed indices with these questions about how the research work is organized as defined in Figure Two. In each instance, the separate indicators were standardized before being combined into an index and then rescaled from 1 to 5.

## Research Findings

The findings are reported in two sub-sections, the first examines the zero-order correlations of each of the indicators of how research is organized and the second then looks at indices that combine the indicators of research processes, networks and technical staff to determine the relative strength of each major theme in explaining each component, critical thought and cross-fertilization, and their combination into the learning index. The components of these three indices are listed in Figure One. The first analysis allows us to understand if there are any interesting substantive differences between specific indicators and their relationships with each learning mechanism and with the index of learning. By isolating which indicator is most important, one can provide advice to research managers and also understand better the second analysis that focuses on the indices. Presumably, the most important component is the main driver. However, we also want to be sure that the index of learning is more than the sum of its components, that is a specific indicator or index has a stronger relationship with the learning index than with each separate component.

### The Attributes of How Research is Organized and Learning

The surprising complexity of research work is readily observable in Table Two where the scientists in STAR have indicated the amount of time they allocated to five research tasks (we have ignored the other category). Also, these five tasks separately are complex combinations of many disparate tasks. Of these five, only research for fundamental understanding has a significant positive impact on mechanisms of learning and also on the index. The small but non-significant relationships of the other tasks, except for organizational work, are to be expected since it is basic research that is most specifically orientated towards the kind of learning that we have measured. Perhaps the most interesting finding is that organizational tasks such as managing contactors and paper work that are bureaucratic requirements because STAR is part of a larger organization, NOAA, has a significant *negative* relationship to two of the indicators of learning and the learning index. This pattern of findings suggests that the index of learning is capturing what we have suggested that it does, namely scientific learning as distinct form other kinds of experiences that can accumulate into knowledge. Thus, hypotheses 1a and 1b are supported.

What fundamental research means varies by the nature of the disciplinary field and then even by the goals of the particular research organization. For the disciplinary field of geophysicists and the mission of STAR, fundamental research has four different kinds of interpretations. As can be seen in Table Three, only one of these specific objectives, namely the review of models, leads to learning as measured by these mechanisms, and then only with cross-fertilization and within-project communication. Contrary to our hypothesis 2a, the development of new algorithms does not produce any learning. The larger conclusion to draw from this table is that most of the associations are essentially zero. Given the lack of a relationship between reviewing models and critical thought, hypothesis 2b, is only partially supported. It would appear that the more important relationship is the time spent on fundamental research and not which research objective within the context of geophysical sciences.

Once we move to research process tasks, we find that the zero-order correlations become much stronger (Table Four). All three of them have not only significant relationships with each learning mechanism, with the single exception of the correlation between creativity and project communication, but perhaps more importantly, the association with the index of learning is stronger than with its components for two of the three processes, suggesting the advantage of constructing such an index. *Of these three processes, it is challenge that has by far the strongest impact on learning.* Surprisingly, at least for us, it is creativity that has the weakest association of the three. This has interesting implications for managers of research projects. It suggests that one learns more by tackling difficult problems than by engaging in incremental or normal science. Another interesting observation is that for all three research process tasks the association with critical thought is ever so slightly stronger than the one with cross-fertilization, although these differences are not statistically significant. The three hypotheses, 3a, 3b, and 3c, are thus supported. When compared with the relatively meager findings about the nature of the research, these findings lead to us to a critical conclusion. *It is not the time spent on research or the specific objective but how the time is spent regardless of the amount that simulates learning.*

The measure of research autonomy also has a significant correlation with each of the learning indicators and to the index of learning (Table 4). As with the other process variables the highest correlation with challenge is the largest, but the correlation with project communication is only slightly smaller. Hypothesis 4 is thus supported.

A similar set of interesting findings about the kinds of collaborative networks is to be found in Table Five. As before, the strongest association is with the index of learning in comparison to individual components, with two exceptions – teamwork on projects and the frequency of external networks are slightly more closely correlated with good project communication than with learning. The difference between the first and second indicator of networks is between collaboration within the same research project and collaborations with researchers in other projects. Hypothesis 5a combined these two ideas; as can be seen both are supported. However, it is interesting in this context to observe that the correlations suggest that sharing with other project teams produces greater cross-fertilization than within-project teamwork. While this may seem obvious, it is still worth demonstrating. Although hypothesis 5b, external networks, is supported, it is interesting to note that it has the weakest correlation with learning of the different measures of teamwork and communication. It is here that one might have expected a much stronger impact on cross-fertilization than with total project communication. This reflects the fact that not all of the scientists are involved in external relationships.

Equally interesting and in contrast to the previous table, the attributes of collaboration have stronger associations with cross-fertilization than with critical thought. In the case of teamwork and networks with other projects, which has an association of .33 with critical thought and .56 with cross-fertilization, the difference is quite large.

In the theoretical framework, we had suggested that for science, the quality of the technical staff is important and should be considered as part of the way in which research is organized. While the sociology of science literature has emphasized the importance of the collaborating scientists, the technical staff has been ignored. In disciplines such as geophysics, the quality of technical staff is very important because of the large amounts of equipment involved in measuring geophysical properties. Therefore, it is not surprising that the quality of this staff does impact on learning. The last attribute, the mix of specialties, again points in the general finding in the management of innovation literature where crossfunctional teams are related to innovation. Hypotheses 6a, and 6b are well supported in this table.

Following up on this point about the mix of specialties, one could go further and argue that many of the measures in Table Five are stating that diversity increases cross-fertilization, which is what leads to innovation (Hage and Meeus, 2006). Total project teamwork is more important than the individual project on which a scientist is working. Communication with management is more important than communication within the project. The one major exception to this line of reasoning is external networks but, as we have noted, not all of the scientists work with other agencies.

This paper began with the idea that the amount of time spent on fundamental research and even the objective of this research would be related to learning. Apparently this is not the case. But the follow-up observation is perhaps more interesting. It is not the amount of time spent nor the objective but instead how time is spent (processes of research) and with whom (kinds of networks and the nature of the technical staff) that affect learning. We now need to explore which of these major ways of describing the organization of research is most critical.

**The Relative Importance of Attributes Describing the Organization of Research**

To explore the relative importance of these different ways of describing the organization of research, we have constructed indices that add the various attributes together as indicated in Figure One. To give approximately equal weight to each index, we have used three measures of collaborative networks that make the most theoretical sense -- within-project teamwork, cross-project teamwork, and external networks -- all of which are measures of diversity. We have only two indicators for the technical staff. We experimented with constructing an index combining the amount of time spent on fundamental research with the objective of reviewing models, but this did not explain much variation even in isolation and in the multivariate analysis its effect approaches zero;therefore it is not reported here.

Regression coefficients of the three indices and autonomy are reported in Table Six along with the amount of variance explained. As can be observed, a substantial amount of the variance of the components is explained and the explanation of the learning index is quite robust. The process variables for describing tasks and autonomy to make decisions are the strongest predictors of critical thinking, but in general, the best predictor is our index of collaborative networks, which we have suggested is really a proxy for diversity of disciplines or multi-disciplinarity. And despite the presence of the other indexes, the index of technical staff still contributes to the explanation of cross-fertilization and the learning index. Similarly, research processes contributes except for the one instance for the component of cross-fertilization.

## Conclusion and Discussion

The study of how applied scientists in a mission agency learn opens, we think, a number of new and interesting questions. This paper has focused on four mechanisms of learning, namely the amount of critical thought and the amount of cross-fertilization, that scientists report having in the context of their daily work, and the quality of communication on their projects and with their management. These are only four mechanisms for learning and in future work more should be added. Some might question that we have separated mechanisms of learning from the consequences of that learning, such as geophysical papers or satellite products but this approach has several advantages. The first and foremost is that it allows us to explore the equation knowledge plus learning equals new knowledge or innovation (Hage and Meeus, 2006). The second may almost seem a contradiction to this, namely that not all learning leads to new knowledge. Indeed, the amount of learning involved in the development of different papers or products varies enormously. Thus there is some advantage in focusing on the amount of learning that occurs independent of its consequences for either innovation or productivity. And given the different kinds of objectives of the nine branches within STAR allows us to more easily compare across them. A major limitation of our method is that it is measuring scientific learning and not organizational learning as such.

As we suggested at the beginning of this paper, it is perhaps better to ask what in research prevents learning. One finding about this is that the time allocated to organizational work has a negative influence. Furthermore, other research tasks, except work on fundamental problems, have little effect. Since the amount of time spent writing contracts, supervising them and providing many reports for NOAA is negatively related to the amount of learning, we have more confidence that our cognitive approach is capturing scientific learning and not just the accumulation of experience as such. Despite these findings, we suggest the first and perhaps the most interesting finding is how we have measured research work, indicating how complex is the work of scientists and that research work has to be divided into separate tasks that vary in in their likelihood of producing learning.

And much to our surprise, while the amount of time allocated to doing fundamental research has some association to our learning index, it is only a weak predictor of learning and in a multivariate model has no effect. As we have suggested, it is indeed the case that one can become more proficient at preparing reports and supervising contractors but this is not the kind of learning that is our concern in this paper. In other research, one might want to measure these other kinds of learning but our objective is to call attention to the importance of scientific learning as a very special and important category of learning.

The second major finding is while the amount of time allocated to fundamental research is not that important and the specific kind of objective in this research has almost no impact, *it is how the time is spent and with whom the time is spent that makes a difference*. In these findings lie some important recommendations for scientific managers. Spending time on challenging problems produces the most learning as we have measured it.

We measured three kinds of networks – project, cross-project and external. These contribute to learning and are especially important for good communication on project teams and with management, which is consistent with a large product development literature that has focused on outcomes (Brown and Eisenhardt, 1995; Keller, 2001). We separated out one category of project team members in measuring the quality and mix of the technical staff; they do have an effect on how much scientists learn, something which has not received much attention.

Finally, the last finding worth emphasizing is that in general and perhaps quite expectedly, when one examines the multivariate analysis, critical thought is influenced more by how the research time is spent and autonomy and cross-fertilization by whom it is spent with, external collaborators and quality technical staff. Of these indices, networks is generally the more powerful, followed by research processes and autonomy. These findings need to be replicated among geophysicists in other research organizations than STAR (NOAA itself has a number of distinct research entities) and among other broad disciplines because one could easily imagine that learning patterns vary considerably. Regardless of this variation, knowing how to increase the amount of scientific learning is important and especially in the context of public research organizations such as STAR dedicated to creating new services for the benefit of society.

**Table One: Mean Learning Scores By Wave and Learning Mechanism**

| | ***Learning Mechanism and Index of Learning Means***[a] | | | | |
|---|---|---|---|---|---|
| ***Year*** | **Critical Thought** | **Cross-fertilization** | **Communication on projects** | **Communication with management** | **Index of Learning** |
| **2005** | **3.67** | **3.05** | **3.81** | **3.12** | **3.33** |
| **2007** | **4.07** | **3.16** | **3.98** | **3.55** | **3.55** |
| **2009** | **3.58** | **3.38** | **4.16** | **3.52** | **3.52** |

**Figure One**
**Indices Describing the Organization of Research**

| ***Construct*** | ***Indicators***[a] |
|---|---|
| *Research Process Tasks* | 1. Sense of challenge<br>2. Time to think creatively<br>3. Freedom to explore new ideas |
| *Collaborative Networks* | 1. Project teamwork<br>2. Cross-project teamwork<br>3. External collaborations |
| *Technical Staff* | 1. Abundance of high quality staff<br>2. Mix of staff |

a. All indicators measured with the following five-point scale as percent of time:
*0 to 20%, 21 to 40%, 41 to 60%, 61 to 80%, and 81 to 100%.* NA was also an option.

**Table Two: Zero-order correlations between research tasks and the amount of learning**

| | *Learning Mechanisms and Index of Learning* | | | | |
|---|---|---|---|---|---|
| ***Research Tasks*** [a] | **Critical Thought** | **Cross-fertilization** | **Commu-nication on projects** | **Commu-nication with management** | **Index of Learning** |
| **Routine technical** | **-0.02** | **0.06** | **0.02** | **0.12** | **0.06** |
| **For fundamental understanding** | **0.20*** | **0.21*** | **0.04** | **0.21*** | **0.21*** |
| **Professional work** | **-0.02** | **0.07** | **0.13** | **0.08** | **0.08** |
| **Organizational work** | **-0.15** | **-0.26**** | **-0.10** | **-0.29***** | **-0.25**** |
| **Education, outreach** | **0.07** | **0.09** | **-0.07** | **0.06** | **0.05** |

a. Scientists reported the actual percent time that they spent in each of these five tasks plus an other category that few selected.
b. * p < .-5, ** p < .01, *** p < .01
c. These results are sensitive to the inclusion/exclusion of five cases that reported spending 0% of their time in fundamental research. Three of them did not answer the question on the distribution of research time; two of them reported spending 100% of their time on “other” research tasks. In this table we have excluded these five.

**Table Three**
**Fundamental Research Objectives and the Amount of Learning**

| | ***Learning Mechanisms and Index of Learning*** | | | | |
|---|---|---|---|---|---|
| ***Research Objective***[a] | **Critical Thought** | **Cross-fertil-ization** | **Commu-nication on projects** | **Commu-nication with management** | **Index of Learning** |
| **Causes of errors** | **-0.09** | **-0.04** | **-0.01** | **-0.01** | **-0.05** |
| **Improve algorithms** | **-0.04** | **-0.09** | **0.03** | **-0.05** | **-0.05** |
| **Review sensor designs** | **0.00** | **-0.12** | **-0,05** | **-0.10** | **-0.09** |
| **Review models** | **-0.01** | **0.27*** ** | **0.20*** | **0.13** | **0.19*** |

a. Scientists reported what percent of their time was allocated to each of these different kinds of basic and applied research objectives common in STAR.

b. * p < .05, ** p < .01

**Table Four**
**Research Processes and the Amount of Learning**
**Zero-order correlations**

| | ***Learning Mechanisms and Index of Learning*** | | | | |
|---|---|---|---|---|---|
| ***Research Processes*** | **Critical Thought** | **Cross-fertilization** | **Commu-nication on projects** | **Commu-nication with management** | **Index of Learning** |
| **Challenge** | **0.47*** ** | **0.46*** ** | **0.41*** ** | **0.44*** ** | **0.56*** ** |
| **Creativity** | **0.23** ** | **0.19* ** | **0.13** | **0.33*** ** | **0.28** ** |
| **Freedom to explore** | **0.36*** ** | **0.33*** ** | **0.19* ** | **0.40*** ** | **0.41*** ** |
| **Autonomy** | **0.46*** ** | **0.25** ** | **0.27** ** | **0.43*** ** | **0.45*** ** |

a. * p < .05, ** p < .01, *** p < .001

**Table Five**
**Networks, Quality of Staff and the Amount of Learning:**
**Zero-order Correlations**

| | ***Learning Mechanisms and Index of Learning*** | | | | |
|---|---|---|---|---|---|
| ***Kind of Networks and Quality of Staff*** | **Critical Thought** | **Cross-fertilization** | **Commu-nication on projects** | **Commu-nication with management** | **Index of Learning** |
| **Project teamwork** | **0.34*** ** | **0.38*** ** | **0.68*** ** | **0.46*** ** | **0.59*** ** |
| **Cross-project teamwork** | **0.33*** ** | **0.56*** ** | **0.45*** ** | **0.49*** ** | **0.58*** ** |
| **External networks** | **0.20* ** | **0.28** ** | **0.42*** ** | **0.37*** ** | **0.40*** ** |
| **Quality of technical staff** | **0.34*** ** | **0.36*** ** | **0.28*** ** | **0.29*** ** | **0.40*** ** |
| **Mix of specialties** | **0.36*** ** | **0.40*** ** | **0.35*** ** | **0.44*** ** | **0.49*** ** |

a. * p < .05, ** p < .01, ***, p < .001

**Table Six**
**Multi-variate Analysis of Research Organization Attributes and Learning**
**Standardized Coefficients**

| | ***Learning Mechanisms and Index of Learning*** | | | | |
|---|---|---|---|---|---|
| ***Research Organization*** | **Critical Thought** | **Cross-fertilization** | **Commu-nication on projects** | **Commu-nication with management** | **Index of Learning** |
| **Intercept** | **0.00** | **0.00** | **0.91*** | **-0.99*** | **-0.28** |
| **Research processes** | **0.33***** | **0.25**** | **0.08** | **0.35***** | **0.26***** |
| **Networks** | **0.23*** | **0.47***** | **0.65***** | **0.53***** | **0.51***** |
| **Technical staff** | **0.11** | **0.18*** | **0.07** | **0.06** | **0.11*** |
| **Autonomy** | **0.39***** | **0.01** | **0.05** | **0.28**** | **0.18**** |
| **Variance explained (adj.)** | **0.35** | **0.36** | **0.46** | **0.48** | **0.62** |

a. * p < .05, ** p < .01, *** p < .001