

Vanguard research | Megatrends

# How America innovates



#### **About the Megatrends series**

Megatrends have accompanied humankind throughout history. From the Neolithic Revolution to the Information Age, innovation has been the catalyst for profound socioeconomic, cultural, and political transformation. The term "Megatrends" was popularized by author John Naisbitt, who was interested in the transformative forces that have a major impact on both businesses and societies, and thus the potential to change all areas of our personal and professional lives.

Vanguard's "Megatrends" is a research effort that investigates fundamental shifts in the global economic landscape that are likely to affect the financial services industry and broader society. A megatrend may bring market growth or destroy it, increase competition or add barriers to entry, and create threats or uncover opportunities. Exploring the long-term nature of massive shifts in technology, demographics, and globalization can help us better understand how such forces may shape future markets, individuals, and the investing landscape in the years ahead.

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#### Megatrend

#### **How America innovates**

- We expect the U.S. economy to experience its fastest level of productivity growth in decades over the next several years. Although official productivity measures have been anemic since the global financial crisis, our analysis reveals that invaluable discoveries were happening in less-commercial research disciplines, requiring time to diffuse into commercial applications.
- The origination of innovative research in the United States has become more diversified as technology has broadened network effects beyond geographic parameters. Additionally, the geographic and ethnic diversity of research collaborators has improved markedly, contributing to the recent increase in groundbreaking innovation.
- Innovation begets higher productivity growth, which in turn facilitates higher wages and better living standards. Higher productivity growth may also lower the risk of stagflation as monetary policy tightens in most developed economies.

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#### Introduction

In early 2020, shortly before COVID-19 was declared a pandemic, Vanguard published the research paper The Idea Multiplier: An Acceleration in Innovation Is Coming (Davis et al., 2020). The report was the culmination of a years-long effort to better understand what drives innovation and when—or if—we might escape the productivity malaise that set in after the 2008 global financial crisis. Tracking academic paper citations, one of the earliest visible stages of idea generation, we constructed a time series of idea generation and sharing and found that they were statistically significant leading indicators of productivity. We also found that although great ideas may be getting harder to find, the global sharing of ideas accelerated by technology and globalization has caused a rapid growth of new, groundbreaking ideas in recent years, suggesting a productivity surge in the first half of the 2020s.

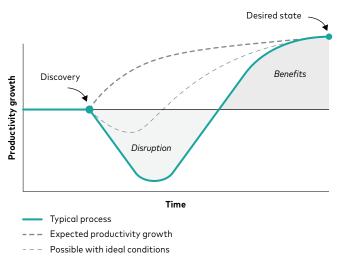
Plenty has changed since the paper's publication, but the importance of innovation and how it improves our daily lives has not. Expanding on this research, we have analyzed what other forces determine idea generation, the potentially monumental innovations we're monitoring, and how knowledge networks have evolved in a global and diverse knowledge economy.

## General-purpose technologies and cross-industry idea sharing

A general-purpose technology (GPT) is an innovation significant enough to alter an entire economic landscape. Several examples likely come to mind: the steam engine, internal combustion, electricity, computers, and artificial intelligence. GPTs don't necessarily have to be physical innovations; lean production practices are heavily credited with Japan's post-World War II resurgence and were replicated throughout much of the developed world in the 1980s and 1990s, narrowing Japan's manufacturing competitive advantage (Helper and Kleiner, 2009). The irony of GPTs is that as innovative as they may be, they often result in lower near-term productivity growth. This is referred to as the productivity J curve (Figure 1), wherein through both mismeasurement and the creative destruction emanating from an economy-altering innovation, productivity growth is underwhelming in the years immediately after a GPT discovery.1

FIGURE 1.

The inconvenient truth about innovation



Source: Vanguard.

<sup>1</sup> Creative destruction refers to the dismantling of existing, or traditional, business practices to make way for an innovative, more productive process.

An intuitive way to think of this delay between GPT discovery and economic productivity growth is the switching costs, both in time and capital resource allocation. For instance, the integration of electricity into manufacturing, which facilitated 24-hour production along with a slate of other productivity enhancements, took decades to complete (Goldfarb, 2002).<sup>2</sup>

This also helps to explain why the 1990s information technology revolution, as monumental as it seemed, did not immediately predate a productivity boom on a scale that the innovation's significance would have hinted (Solow, 1987).<sup>3</sup> In fact, the productivity effects of the nearly three-decade-old IT GPT are still materializing (Remes, Mischke, and Krishnan, 2018), in large part because of e-commerce and remote work in the COVID-19 age. Although the technologies enabling remote work, such as computers and videoconferencing, have existed for decades, the prevalence of remote work plateaued in the early 2000s because of a variety

### A slow, then rapid, adoption of remote work

The onset of the COVID-19 pandemic in 2020 forced many workplaces to temporarily close, triggering a massive shift to remote work. According to the U.S. Census Bureau, the percentage of U.S. workers working at least one day a week at home marginally rose from 7% in 1999 to 9.5% in 2010. The U.S. Bureau of Labor Statistics estimates that in May 2020, roughly 40% of all workers were working from home at least occasionally. At the end of 2020, this percentage was closer to 30%. Post-COVID expectations for the percentage of the workforce with remote work flexibility are around 40% (Lund et al., 2021).

of social factors, only to be widely adopted as a result of COVID. One can only fathom how COVID-containment approaches would have differed just 30 years ago because of technological constraints.

The delay between GPT discovery and economic implementation may be driven by cultural and behavioral factors, or the time needed for other industries to learn how to integrate the new technology into their processes. This crossindustry relevance separates a GPT from an industry-specific innovation, but the difference is not always evident in the early years following discovery or may depend on another technological discovery. Initial skeptics of personal computers who viewed the innovation as limited to hobbyists may have been correct, if not for the internet.

Knowledge is a necessary condition of technology, and just as GPTs realize their full potential by integrating with the wider economy, some knowledge discoveries—termed frontier knowledge—propel further discovery in farreaching, sometimes seemingly unrelated, research disciplines. This complicated relationship can obscure the significance of present knowledge discovery and cause us to overlook groundbreaking research and discovery in less-commercial industries.

<sup>2</sup> Goldfarb wrote, "Indeed, a large share of electrification and subsequent productivity gains occurred in the 1920s, a full forty years after Edison installed the first electric networks."

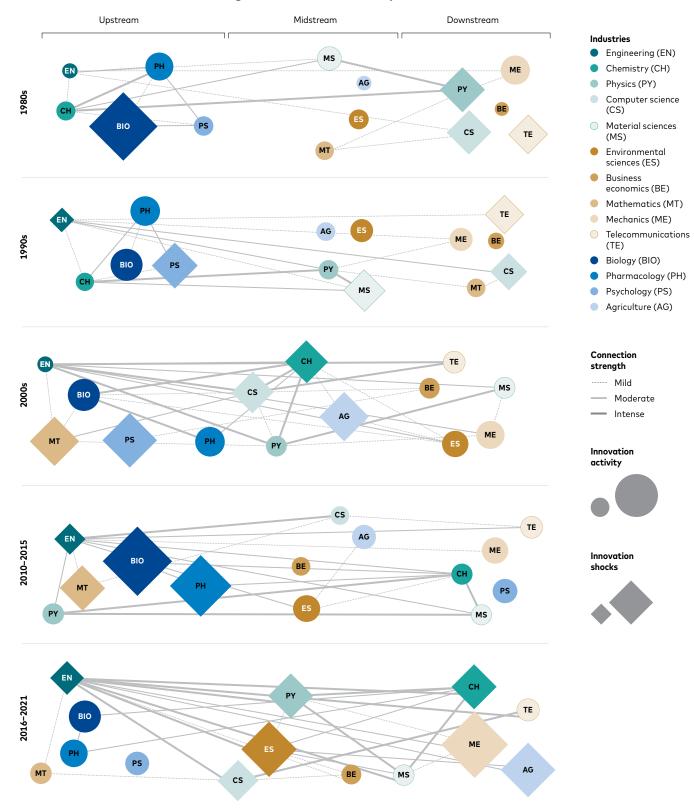
This is sometimes referred to as the Solow computer paradox, after Robert Solow's 1987 remark that "you can see the computer age everywhere but in the productivity statistics." Several years later, U.S. productivity growth moderately rose, averaging 0.9% from 1992–1999.

Figure 2 demonstrates this concept by tracking the progression of significant ideas across research disciplines. As in our *Idea Multiplier* paper, we start the filtering process by tracking the most-cited research papers across a selection of disciplines. The filtering criterion is not perfect—some significant ideas can sit stagnant and uncited for decades before finding an ultimate application—but it's a suitable proxy for the highest-potential ideas. We discover that biology, engineering, and mathematics are upstream disciplines and therefore are more common originators of frontier knowledge, with their discoveries branching into other disciplines before finding a commercial application.

In essence, upstream disciplines often produce the frontier knowledge necessary for downstream disciplines to expand upon and commercialize. This can cause a disconnect between the actual level of innovation and discovery occurring in scientific disciplines and headline economic productivity measures borne from commercial utilization. In the United States, productivity growth has been declining since the 1990s but has been particularly disappointing since the global financial crisis. Many explanations have been posited to explain this slowdown, but our research suggests another possible explanation: Innovations over the past 15 years were primarily frontier discoveries or those that occurred in upstream disciplines and needed time to find their downstream, commercial applications.4

<sup>4</sup> Research by Marx and Fuegi (2020) finds that the percentage of patent applications citing an academic article on their first page rose from 6.7% in 1976 to 25.6% in 2018.

FIGURE 2.
Innovation shocks are occurring in downstream disciplines



**Notes:** Connection strength is measured by the number of normalized academic citations connecting two disciplines. (Normalized citations control for a discipline's publication volume.) Innovation activity is measured via our Idea Multiplier metric, which captures the intensity of citation activity in select industries. Innovation shocks are structural breaks in an industry's citation activity. (For more information on structural changes in linear regression models, see <a href="https://cran.r-project.org/web/packages/strucchange/strucchange.pdf">https://cran.r-project.org/web/packages/strucchange/strucchange.pdf</a>.) The size of the shapes implies the volume of innovation.

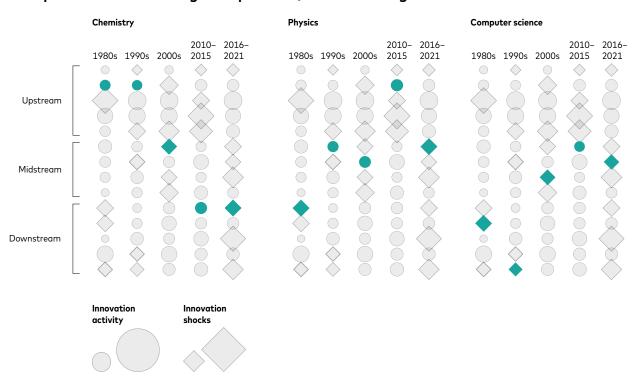
**Sources:** Vanguard calculations, based on data from Clarivate Web of Science.

The placement of disciplines on the upstream/downstream gradient has moved over time, based on fundamental economic transformations, as shown in **Figure 3**. Before the 2000s, computer science was a downstream discipline, relying on frontier knowledge from other disciplines to construct commercial applications. However, as computers were integrated throughout the economy, computer science discoveries became necessary for innovation in other fields. Inversely, chemistry

was an upstream discipline before the turn of the millennium, but discoveries in the energy sector have moved it toward the downstream side. Regardless of location on the upstream/downstream gradient, research disciplines are more likely than ever to cite research outside of their field—three times more likely than they were in 1980. Therefore, while it's likely that good ideas are becoming harder to find, a good idea today can crosspollinate with many more ideas than previously possible.

FIGURE 3.

Disciplines can move along the upstream/downstream gradient



**Notes:** Location on the upstream/downstream gradient is measured by external citations (how often other disciplines cite a piece of research) and external references (how often a piece of research cites other disciplines' research). An industry with high external citations and low external references is an upstream discipline, and an industry with low external citations and high external references is a downstream discipline. The size of the shapes implies the volume of innovation. The green shapes represent the location of the particular discipline.

Sources: Vanguard calculations, based on data from Clarivate Web of Science.

#### Where is innovation occurring?

By tracking idea progression across industries, we can detect scientific research that has the potential of becoming frontier discoveries and research that has more immediate commercial viability. In our *Idea Multiplier* paper, we identified transportation and civil engineering, material sciences, and mechanics as three industries with the most noticeable increases in idea generation and sharing, suggesting a productivity surge in these industries. This holds true today, but with new technological capabilities we can dive deeper into the subresearch fields and subject areas that are experiencing measurable innovation shocks. These shocks are in both frontier knowledge

responsible for longer-term potential productivity and commercial innovations whose productivity implications we may experience in short order.

In doing so, we find some unsurprising, burgeoning research fields such as environmental sciences and public, environmental, and occupational health, as well as some less obvious disciplines, including chemistry, surgery, and food science technology (Figure 4). Tracking the highest-potential ideas within these fields, we can identify associated fields that are supplementing this research through either downstream or upstream contributions. Lastly, we isolate specific fields of study that are driving these innovation shocks, such as liquified solar energy storage, environmentally friendly food packaging, and advanced brain tumor detection.

FIGURE 4.

A look at recent innovation shocks

	Field	Associated fields	Specific fields of study	
	Environmental sciences	Physics		
		Microbiology	Supercapacitors, liquid solar energy, graphine superlattices, antibiotic resistance genes, <b>long-cycling lithium batteries</b>	
$\bigotimes$		Nutrition dietetics		
		Material sciences		
		Surgery	<del></del>	
	Public, environmental, and occupational health	Development studies	Antimicrobial resistance, malaria treatment and prevention, statistical research design	
Ŏ.		Orthopedics		
`		Tropical medicine		
	Food science technology	Chemistry		
9		Psychology	Phenolic compounds, polyphenols, biopolymer  food packaging	
		Forestry	— 1000 packaging	
	Chemistry	Mineralogy	Nanocrystals, polymeric photocatalysts, nanotechnology pesticide delivery	
····		Oceanic engineering		
		Agriculture		
0	Surgery	Engineering	<b>Brain tumor detection</b> , neurological disorders	
13		Cybernetics		
_		 Neuroimaging		
	Physics, optics	Limnology	Solar cell efficiency	
4		Nuclear physics		
-v		Soil science		
	Biomedical engineering, genetics	Material sciences	Genetic sequencing, DNA damage response genes, <b>sweat-based wearable sensor arrays</b> , gut microbiology	
		Microbiology		
*		Nanotechnology		

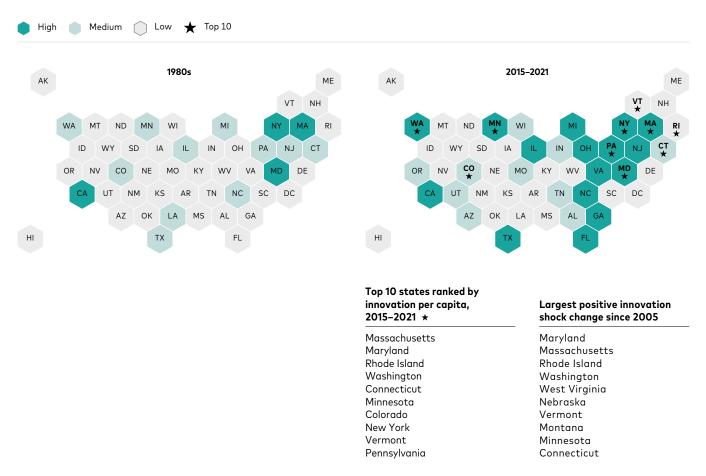
**Note:** Innovations in bold indicate near-term commercial viability; nonbold indicates frontier discoveries. **Sources:** Vanguard calculations, based on data from Clarivate Web of Science, as of December 31, 2021.

Just as geographies can have distinct economic competitive advantages based on natural resources, demographics, and human capital, they also can have competitive knowledge advantages determined by their educational infrastructure and existing knowledge stocks (Ellison and Glaeser, 1999). **Figure 5** shows the U.S. states with the most recent innovation shocks and those that have experienced the largest

increases in innovation since 2005. Although concerns have arisen in recent years of a winner-takes-all economy, wherein top performers are able to scale faster and become more dominant, scientific discovery within the U.S. has become more diversified over the past three decades. This is an encouraging sign that technology is enabling diversity of the sources of both frontier knowledge and commercial innovation.

FIGURE 5.

More states are becoming hubs for innovation



**Note:** The U.S. map illustration represents aggregate innovation shocks (not population-adjusted innovation shocks). **Sources:** Vanguard calculations, based on data from Clarivate Web of Science, as of December 31, 2021.

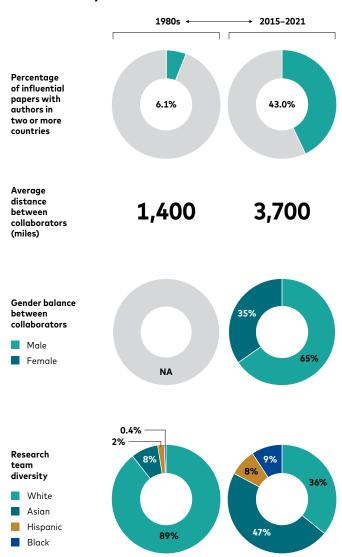
#### The power of diverse perspectives

No assessment of innovation trends would be complete without acknowledging the significant compositional changes of research teams over recent decades. At the highest level, this is represented by the increase in cross-country knowledge sharing via technology and globalization. The rise of the global middle class has also drastically increased the number of global researchers, from 6.2 million in 2003 to 8.9 million in 2018, a 43% increase. According to our calculations, the increase in international knowledge sharing since 1990 is responsible for more than half of all new scientific discoveries since that time (Davis et al., 2020).

But there's more to the story than researchers from one country building upon knowledge of those from another country. International collaboration within research teams has also risen drastically. As Figure 6 shows, the percentage of influential papers with authors in two or more countries has increased sevenfold since 1980, while the average distance between any two collaborators has more than doubled.6 A byproduct of this collaboration is a rise in ethnic and gender diversity within research teams. In our analysis, we find that a highly diverse research team is 2.4 times more likely to produce a frontier discovery and 3.8 times more likely to discover a commercial innovation shock than a low-diversity research team.7 (See the Appendix for results.)

#### FIGURE 6.

#### The diversity of research teams has evolved



Notes: Our gender-matching algorithm requires first names, which weren't published in academic journals prior to the mid-2000s. Gender categories were determined by classification criteria in the underlying data sets. To identify ethnicity, we used U.S. census data, Florida voter registration data, and Wikipedia data using the Ethnicolr Python statistical package created by Sood and Laohaprapanon (2018). The granularity depended on the data set. The census data we use in the model categorizes ethnicity as Non-Hispanic White, Non-Hispanic Black, Asian, and Hispanic. The Florida voter registration data set includes nine categories of ethnicity: American Indian or Alaskan Native, Asian or Pacific Islander, Non-Hispanic Black, Hispanic, Non-Hispanic White, Other, Multiracial, and Unknown. We restrict our attention to the four largest racial categories in the United States, Asian, Black, Hispanic, and White, because of limited data points for the other categories. Percentages may not total 100% because of rounding.

**Sources:** Vanguard calculations, based on data from Clarivate Web of Science, Wikipedia, the Florida voter registration database, and the U.S. Census Bureau.

- 5 According to the UNESCO Science Report; available at https://unesdoc.unesco.org/ark:/48223/pf0000377250.
- 6 Influential papers are defined as those represented by the 10,000 most cited articles.
- 7 High-diversity research teams are defined as those that satisfy at least two of the following three conditions: researchers in two or more countries, gender heterogeneity, and ethnic heterogeneity. Low-diversity research teams are defined as those that satisfy none of these conditions.

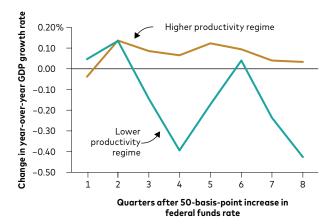
## Higher productivity may lower stagflation risk

As many developed-market central banks, and particularly the Federal Reserve, find themselves battling decades-high inflation amid a rather unique macroeconomic backdrop, stagflation concerns have resurfaced. Some observers fear that as the Fed aggressively raises interest rates in 2022 (likely ending the year close to a 3% federal funds rate), the U.S. economy will slow. Meanwhile, elevated energy prices and supply chain disruptions will impede the natural deflationary pressures of a slowing economy—so growth will slow, but inflation will remain elevated.

It's natural to assume that raising rates will slow the economy. That's the intent behind raising rates—reducing aggregate demand to match supply and thereby lowering inflation. But in reality, the economic relationship is more complicated. For example, raising interest rates can also improve the efficiency of capital expenditure allocation, promote foreign direct investment, and discourage risky lending, all of which are tailwinds for long-term sustainable economic growth (Cao and Illing, 2015; Sujianto et al., 2020; International Monetary Fund, 2015).

Another key determinant of how the U.S. economy reacts to rising interest rates is productivity growth. As shown in **Figure 7**, the GDP response to rising interest rates varies depending on the productivity environment, with economic growth less sensitive to rising rates during a period of higher productivity growth.

# FIGURE 7. Higher productivity growth mitigates the GDP response to higher interest rates



**Notes:** *Higher productivity regime* is defined as the three-year moving average total factor productivity (TFP) growth exceeding the prior three-year moving average TFP growth. *Lower productivity regime* is defined as the three-year moving average TFP growth lagging the prior three-year moving average TFP growth. A basis point is one-hundredth of a percentage point.

**Sources:** Vanguard calculations, based on data from the Federal Reserve Bank of St. Louis FRFD database

<sup>8</sup> Stagflation is defined as stalling or declining economic growth coupled with high inflation.

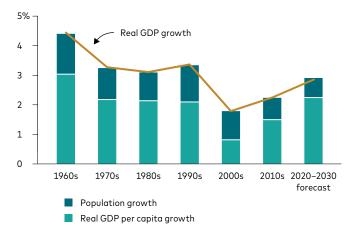
## New ideas and a diverse perspective are driving innovation

Our conviction in the optimistic productivity outlook we expressed in our 2020 *Idea Multiplier* paper has only increased as businesses were forced to rapidly evolve during the COVID-19 pandemic. We now expect U.S. GDP per capita growth to average 2.0%–2.5% from 2020 to 2030 (Figure 8), a pace we haven't seen in decades and a positive development for wage growth, asset returns, and economic opportunity (Davis et al., 2020). This productivity boom has been bubbling under the surface following the global financial crisis, supported by research in less visible upstream disciplines that needed time to permeate downstream and find their commercial utility.

There's also reason to be optimistic that the economic benefits of this productivity surge will be more widespread as the concentration of innovation shocks has declined in recent years. Globalization and technology facilitated international knowledge sharing, but just as importantly, they changed the composition of research teams by increasing intellectual and demographic diversity, which our research shows increases the likelihood of producing frontier and commercial innovation.

#### FIGURE 8.

## Higher productivity growth may result in the fastest-growing decade for U.S. GDP since the 1990s



**Sources:** Vanguard calculations, based on data from the U.S. Census Bureau, Thomson Reuters, the Federal Reserve Bank of St. Louis FRED database, and Clarivate Web of Science.

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#### **Appendix**

#### FIGURE A-1.

#### Effectiveness of research teams

	Low diversity	Medium diversity	High diversity
n	13,531	11,370	10,300
Frontier discovery (%)	454 (3.3%)	464 (4.0%)	842 (8.2%)
Commercial innovation (%)	351 (2.6%)	391 (3.4%)	1,017 (9.9%)

**Notes:** High-diversity research teams are defined as those that satisfy at least two of the following three conditions: researchers in two or more countries, gender heterogeneity, and ethnic heterogeneity; medium-diversity research teams are defined as those that satisfy one of these conditions; and low-diversity research teams are defined as those that satisfy none of these conditions. Diversity classifications are exclusive. The initial data set includes only highly cited research papers; listed percentages are from this refined set. Commercial innovation must have citations in the 95th percentile once adjusting for research age and research discipline. Frontier discoveries have a citation/reference ratio in the 95th percentile. Innovations can be considered both a commercial innovation and frontier discovery; this occurred 1,061 times in our data set. We control for a paper's age and research discipline because older papers have a longer time period to collect citations and disciplines have varied citation patterns. This attempts to minimize any bias from potential reverse causality, wherein highly cited fields may result in more-diverse research teams than less cited fields.



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