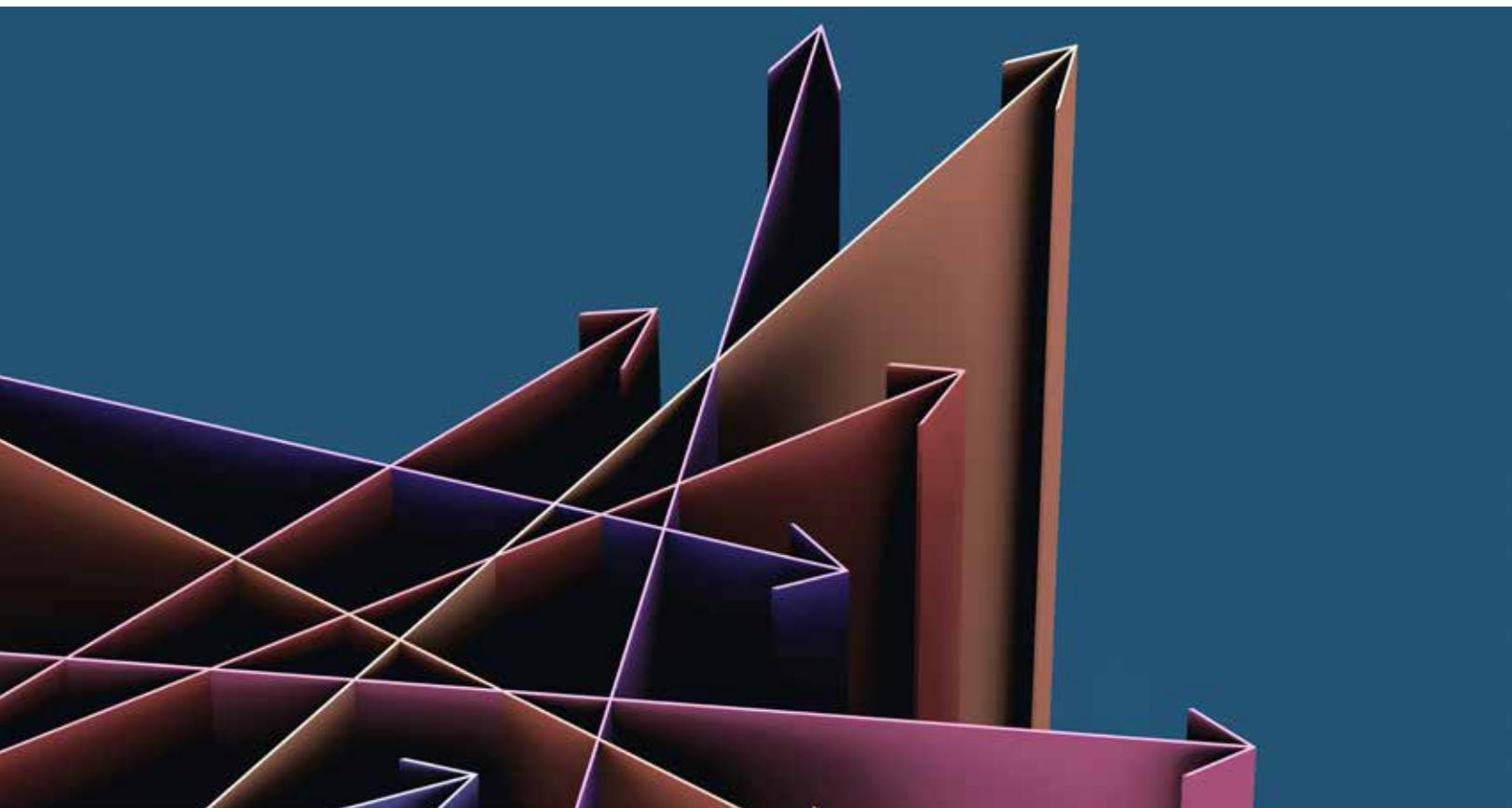


Strategy & Corporate Finance Practice

Predictive sales forecasting: Is your finance function up to code?

Some companies are using automation, machine learning, and advanced analytics to make the crystal ball clearer. Here's how your company can do the same.

by Holger Hürtgen, Frank Plaschke, Karolina Sauer-Sidor, and Nils Wittmann



Most executives will tell you that when shaping business plans and strategy, forecasts can serve as a great counterweight to gut feelings and biases. Most will also admit, however, that their forecasts are still notoriously inaccurate.

There are signs, however, that some finance teams' early experiments with automation, machine learning, and advanced analytics are changing the game—particularly for demand planning and sales-and-revenue forecasts. A chemical distributor, for instance, increased its sales by 6 percent because of its ability to conduct more accurate and frequent forecasts that informed its allocation of resources. A retailer and a global engineering-consulting firm both reported similar benefits from advanced analytics, as measured by user responses to new products and by changes in profit on income, respectively.

In the wake of the recent economic uncertainty and market volatility, it will become even more important for finance functions to explore advanced analytics and automation. Finance teams will need these techniques to turbocharge their forecasting capabilities. They will need efficient ways to generate and disseminate real-time forecasts that reflect rapidly changing circumstances. Likewise, it will be imperative for financial-planning and -analysis (FP&A) teams to embrace automated dashboards and other digital tools, so that data can be refreshed frequently and encompass multiple perspectives (see sidebar, "Planning during a pandemic").¹

In this article, we clarify the opportunity from advanced analytics and describe the organizational, operational, and leadership capabilities required to use new technologies to generate better, more accurate forecasts. Some leading-edge companies are already well on their way in the journey from fully analog to mostly digital. Their stories and remedies may be particularly illuminating for companies and finance organizations that are still trying to find a path forward.²

Opportunity: Better forecasts

Not all forecasts will be 100 percent correct, 100 percent of the time. No statistical formula can predict the surge, outcome, or exact length of black-swan events, for instance—there will be no data for that. Nor will analytics generate optimal forecasts every time; even companies that currently use data analytics in forecasting acknowledge that context matters. In the wake of COVID-19, for example, streaming-media companies have had to reset their algorithms and data sets to take into account the unpredictable effect of quarantines on content consumption. Companies in many other industries are doing the same.

In general, however, a company that has a proven track record of accuracy in forecasts can create trust among business leaders about the numbers it generates and the trends they may reveal. This is where the use of models based on automation, advanced analytics, and machine learning make the most sense—particularly as finance teams build forecasts for short-term operations (between three and 18 months) and midterm market demand (one to three years).

The short term. A global manufacturer's demand forecasts were regularly off by 30 percent or more. As a result, planning teams within each of the company's business lines did not trust the numbers and instead chose to follow their gut instincts. By ignoring the centrally calculated predictions, however, they further limited the amount of good outside data they could use to develop market strategies.

The finance function had traditionally relied only on small historical sets of sales data and largely manual reporting processes to establish production baselines and make-to-stock requirements. Over a six-month period, it replaced this approach with a machine learning–based model that incorporated a much richer data set—for instance, details about product life cycles and performance,

¹ Mark Maurer, "Finance teams adapt to closing the books remotely amid coronavirus," *Wall Street Journal*, March 31, 2020, [wsj.com](https://www.wsj.com).

² Frank Plaschke, Ishaan Seth, and Rob Whiteman, "Bots, algorithms, and the future of the finance function," January 2018, [McKinsey.com](https://www.mckinsey.com).

historical growth and sales figures, survey results, and information about external events from various markets.

This change improved the accuracy of the manufacturer's short-term forecasts. The finance organization could quickly generate updated sales profiles based on calendarized orders and information about the macroeconomics of specific geographies. With this information in hand, the company was able to reduce inventories and product obsolescence by 20 to 40 percent, depending on the SKU. It was no longer simply reacting to market fluctuations; it was proactively managing them. It was also able to capture an additional 5 percent in sales because it was constantly meeting demand across most markets.

Planning during a pandemic

The COVID-19 pandemic has disrupted the usual forecasting and planning approaches. Demand patterns for different products and services—consumer goods, especially—have been abnormal, given the uneven spread of the virus and continuing economic and health uncertainties. Models that rely heavily on historical data therefore cannot entirely capture the effects of the crisis on both current operations and into the next normal.

However, some finance teams are using advanced analytics to stress-test their forecasts and scenarios. The technology has allowed them to drill down on the impact of the crisis on specific product categories under different parameters. For instance, one CPG company is using a combination of precrisis data, postcrisis assumptions about business drivers, and consumer-behavior research to model demand for its product categories under various recession scenarios. One early finding showed that the one-year compound annual growth rate in the “canned goods” category changed from –2.7 percent in a business-as-usual setting to 4.2 percent under a deep-recession scenario. The behavior was linked to an abrupt drop in GDP, disposable income, unemployment, consumer-confidence indicators, and other macroeconomic factors. By contrast, other products such as laundry detergent were not influenced as much by the current situation; demand remained similar across all scenarios and assumptions.

The midterm. A category-leading consumer-goods company that sold nine categories of products in more than a dozen countries did not have a unified view of its current sales. The company typically based its financial planning for the next one or two years on the previous year's numbers, so it could not gain meaningful insights beyond its initial predictions. The finance function therefore sought to automate the data-collection process and to combine all data into a single source of truth to be mined for insights.

Using cross-correlation analyses, a team worked with business-unit leaders to identify potential factors affecting demand for each market and category. It found that many of the company's business-unit heads based their forecasting models on hypotheses rather than evidence. One business unit, for instance, had been examining how rainy weather affected sales of its products, but this variable could not be modeled accurately—a look at weather patterns could explain past performance, but it would be very difficult to predict the weather for the next several years.

The finance organization worked with the business-unit leaders to test and evaluate different forecasting models for each country-and-product combination empirically. In relatively stable markets and product categories, simple statistical forecasts based on a handful of historical time series were enough. The more complex markets and product categories—for instance, those in which more than 20 inputs influenced demand—required advanced machine-learning forecasting models.

Under this approach, the manufacturer created more precise forecasts for all countries and product categories and gained greater insight into the key drivers of demand. The variables ultimately included about 100 classic macroeconomic factors, such as real GDP, disposable income, unemployment, and consumption trends, as well as 150 esoteric variables, like Google searches for the company's products, demographic changes, and consumer-confidence indicators.

Given the size and scope of the observations that Google-trends indexes capture, they serve as a powerful proxy for consumer behavior in forecasting

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models. A company can use data from these indexes and machine learning to detect patterns, trends, and seasonality in users' web-search behavior. Then it can feed these data back into its forecasting models to help establish targets. The total number of variables in such forecasting efforts can exceed 1,000.

Implementation: Scaling up

Once opportunities to create value have been identified and benefits targeted, organizations implementing advanced analytics and machine learning at scale must emphasize three basic requirements:

Clean, accessible data. Perhaps more than other functional groups, a finance organization implementing or scaling up an advanced-analytics program must ensure the fidelity and accuracy of data. When business information isn't adequately sourced, aggregated, reconciled, or cleaned, staffers spend more time on tasks that don't add value and less on important strategy-oriented discussions. As one data analyst told us, availability is not an issue in most companies; accessibility is the bigger concern. At one chemical company, for instance, the machine-learning models could not read unorganized data sets, so certain key performance factors were excluded from the results. The data in question had to be cleaned up and reingested, which added time to the modeling process.

Finance leaders must work with IT and the business to set the ground rules for data usage—what good data look like, who owns them, who can access them, and so forth. Finance, IT, and business leaders

must also collaborate to ensure that employees at all levels are trained to understand the systems required to collect, access, and maintain the data.

Operations and organization. It won't matter how clean the data are or how easy they are to access if the finance function doesn't have the right operational and organizational structure to implement advanced-analytics programs. It needs supporting processes and protocols to gather insights from the data, share those insights, and develop action plans in concert with business-unit leaders. These structures might include strategic data environments, such as data lakes, enterprise layers, cloud platforms, visualization tools, and development sandboxes.

The finance team will also need to focus on cultural issues—for instance, by highlighting “lighthouse cases” that might inspire other parts of the business to use advanced analytics. Leaders in one pharmaceutical company started with one small group charged with monitoring data on clinical trials. The company then gave a slightly larger group of users access to these data so it could determine how efficient and effective its clinical-trial process was. Eventually, it built out modules that thousands of users could access.

Talent. The company and the finance team will likely need to hire data scientists, data engineers, and data-visualization specialists. They will probably need to retrain internal staffers to work with data specialists, as well. Otherwise, execution will stall.

In most cases, this will be difficult. Traditional organizations may not be able to lure top digital and finance talent. Smaller companies that do not have

the payrolls to bring on data scientists and financial analysts full time will have to determine how much analytics work to outsource and how much to keep in-house. One consideration is sustainability: models and regressions are never 100 percent stable over time, so they will need to be adjusted continually, which strengthens the case for in-house capabilities. It may be worth convening a small hybrid group of finance and digital professionals to work on no-regrets projects that make the case for deeper investments in digital talent.

In many companies, data governance can involve significant effort, which may be better managed in-house. A global manufacturing company, for example, developed its own in-house programs and certifications for training digital translators and data scientists. The company offers multiple modules and curriculums at all levels of the organization, and more than 300 managers and employees have gone through the program, which mitigated the need for an extended recruiting effort.

Vision: The CFO in the lead

Leaders of companies must have a clear vision of how they will use new technologies. In our experience, CFOs are well positioned to provide that vision and to lead the widespread adoption of advanced analytics. They have most of the necessary data in hand, as well as the traditional quantitative expertise to assess the real value to be gained from

analytics programs. Project teams and senior leaders may suspect that their companies could streamline processes or export products more efficiently, for example, but the CFO can put these ideas in the proper context. At investor days or in quarterly earnings reports, C-suite leaders tend to talk about analytics programs in broad terms—for instance, how they will change the industry, how the company will work with customers differently, or how digitization will affect the financials. What's missing is the impact for investors, and CFOs can supply that. In doing so, they can help fulfill the oft-repeated request, from both senior management and the board, that they serve not only as traditional transaction managers but also as key strategy partners and as value managers.

Of course, CFOs cannot lead digital transformations all alone; they should serve as global conveners and collaborators, encouraging everyone, including leaders in IT, sales, and marketing, to own the process.

CFOs on the cutting edge of advanced analytics are positioning themselves not just as forward-thinking finance leaders but also as valued business partners to other leaders in their companies. Those who aren't will need to think about how analytics programs could change the way they work—and then lead by example.

Holger Hürtgen (Holger_Huertgen@McKinsey.com) is a partner in McKinsey's Düsseldorf office, **Frank Plaschke** (Frank_Plaschke@McKinsey.com) is a partner in the Munich office, **Karolina Sauer-Sidor** (Karolina_Sauer-Sidor@McKinsey.com) is a partner in the Vienna office, and **Nils Wittmann** (Nils_Wittmann@McKinsey.com) is an expert in the Hamburg office.

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