Equipment Financing as an Economic Forecasting Tool: Evidence from ELFA's CapEx Finance Index

The Equipment Leasing & Finance Association

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Executive Summary

Investment in equipment and software both supports current economic growth and raises future economic potential. When businesses replace outdated equipment or add new technology or production capacity, they increase productivity, create jobs and build the future of American industry. However, those capital investments can be expensive, particularly for small businesses. And many companies lack the required cash to fund large purchases; the Equipment Leasing & Finance Foundation's 2024 Horizon Report found that eight out of 10 companies use some form of financing when purchasing software or equipment.[i] It is therefore vital that these companies have access to deep and healthy financial markets to ensure they can acquire the necessary equipment and software to expand their operations and grow the American economy. As of 2023, that market reached $1.34 trillion, or 4.8% of the U.S. economy.[ii]

To track industry conditions, the Equipment Leasing & Finance Association (ELFA) introduced the Monthly Leasing and Finance Index in 2006, which ultimately evolved into the CapEx Finance Index (CFI) survey. It captures real-time conditions in the sector by asking a sample of equipment finance companies about changes in new business volume and industry financial conditions. Those responses are aggregated into a series of statistics that track the overall health of the equipment finance sector.

The CFI has become an integral part of the economic data release cycle and is widely covered by major news outlets. Previous analysis has shown a correlation between CFI data and parts of the Census's Manufacturers' Shipments, Inventories, and Orders (M3) survey. However, to date, no study has explored a deeper statistical relationship between CFI survey data and broader economic indicators. This report employs advanced time series techniques to assess the effectiveness of various CFI measures in enhancing the forecasting of key government statistics. First, regressions are generated to establish a link between CFI data and government data. Then, rigorous out-of-sample testing is used to compare forecast errors for models with CFI data against models that use only traditional autoregressive forecasting methods. Improvements in nowcasting models, which leverage both historical data and same-month data, were also assessed. Both methods exhibit lower forecast errors when CFI data are included in the models.

Here are key takeaways from our analysis of 75 indicator-predictor combinations:

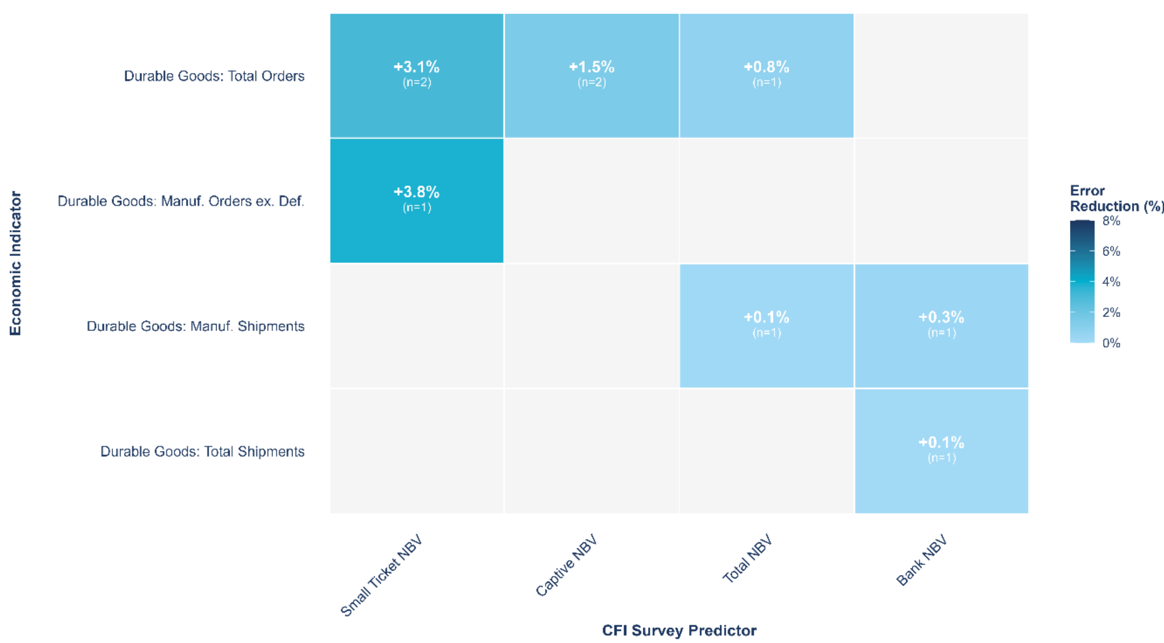
- **Using CFI survey data reduces forecast error relative to baseline models.** Incorporating CFI data into nowcasting models reduces forecast errors in 28% of the specifications that were tested, in both nowcasting and forecasting models. That is higher than the 5% that would be expected by random chance, and a clear sign that CFI data improve forecasting models for key government data.

- **New business volume (NBV) data reduce forecast errors in models that predict shipments of durable goods and manufacturing shipments.** Captive NBV reduces forecast errors for total manufacturing shipments by 7.3% and durable goods shipments by 7.0%. Small ticket NBV performs well across both categories, reducing forecast errors for manufacturing shipments by 4.3% and durable goods shipments by 4.7%, while independent NBV contributes improvements of 2.8% and 3.2%.

- **Small ticket NBV emerges as the most versatile predictor**. The NBV small ticket series achieved the largest nowcasting improvement (5.4% for durable goods orders) and appeared in most models that improved forecast accuracy. This makes intuitive sense, as small-ticket deals are likely to be more diversified and less skewed toward large transactions, making them more representative of small- and medium-sized business activity.

- **The earlier timing of the CFI release improves forecast accuracy for some Census data.** Every month, the final CFI report is released one day before the Census's M3 survey. That potentially allows analysts to leverage the timing of the release to improve predictions by incorporating same-month data into the modeling process (nowcasting). This analysis demonstrates that nowcasting models incorporating CFI data reduce forecast errors by an average of nearly 3.0%, confirming that the earlier release of the CFI report is crucial for enhancing predictions of Census data.

Figure 1. CFI Survey Data Improves Economic Nowcasting
Average Forecast Error Reduction



Notes:

(1) Only indicator-predictor pairs with significant improvements are shown. Gray cells were tested but not significant at the 5% level.
(2) n = the number of significant forecast windows.
(3) Nowcasting uses timely CFI data (available before official economic statistics) to predict current-month economic indicators.

Source: ELFA CapEx Finance Index and Federal Reserve Economic Data (FRED)

Implications for Different Stakeholders

For Economic Forecasters: CFI data improve forecasting of key government data releases that are essential barometers of equipment demand and firm capital investments. This analysis shows that incorporating CFI data reduces forecast errors relative to traditional forecast models. The results are statistically significant and robust, indicating that CFI survey data should be included in the professional forecasters' toolkit when forecasting and nowcasting monthly data from the Census's M3 and Federal Reserve data on commercial loss rates.

For Policymakers: This analysis demonstrates that policymakers can gain deeper insights into the demand for investment goods and financial conditions for financing firms in the commercial and industrial sector, which in turn provides a greater understanding of both current and future economic conditions by incorporating CFI data into their assessments. This is particularly valuable in times of heightened uncertainty, as volatility decreases the accuracy of many traditional economic forecasting methods.

For Financial Institutions: The predictive relationship between equipment finance portfolio quality and broader commercial credit conditions highlights risk management opportunities. The improvement in forecasts of commercial and industrial (C&I) charge-off rates suggests that equipment financing portfolios may serve as an early warning system for broader C&I balance sheet stress. The CFI is also timelier as it is released monthly while the Fed's statistics are released quarterly. This provides financial institutions with more frequent insights that could enhance risk monitoring and management.

For ELFA Members: These results validate the systemic importance of the equipment finance sector to broader economic conditions. Member participation in surveys and questionnaires leads to better analysis and insight for U.S. businesses and policymakers, helping to smooth economic cycles and provide more clarity during periods of uncertainty.

Data Sources and Definitions

The CapEx Finance Index

The CFI aggregates individual survey responses from 25 ELFA member organizations representing a broad cross-section of the equipment finance industry. Participating firms report new business volumes, employment levels, and financial metrics like the percentage of delinquent accounts over 30 days, the charge-off rate, and their credit approval rate.

For research purposes in this paper, survey respondents self-select into three institutional categories:

- **Bank-Owned Finance Company**: A finance company that operates as a subsidiary of a commercial bank. It leverages the bank's capital and funding infrastructure to originate and manage equipment loans and leases, typically serving a range of customer segments aligned with the bank's broader strategic goals.

- **Captive Finance Company**: A wholly or majority-owned subsidiary of an equipment manufacturer, established to provide financing solutions for the purchase of the parent company's products. Captive finance companies support sales by offering tailored financing options to dealers and end-users.

- **Independent Finance Company**: A non-bank, non-captive finance organization that provides equipment financing using capital raised from institutional investors, private equity, and other funding sources. These companies operate autonomously and often focus on niche markets, offering flexible and innovative financing structures, with some funded by private credit.

The CFI survey contains a rich data set of demand indicators and measures of financial conditions. For this analysis, CFI data for new business volumes (NBV), the delinquency rate, and the charge-off rate for the three institution types, as well as an additional breakout for small ticket deals, which groups companies that typically finance transactions below $250,000, were assessed. The small ticket subgrouping is linked to small business demand for equipment and is thus an important barometer of economy-wide demand for capital investments in business equipment.

Economic Indicators

The analysis focuses on the CFI's ability to predict indicators for demand for manufacturing goods, investment, and credit conditions. The monthly manufacturing indicators used in this report are various measures of new durable goods orders, which often lead production cycles by several months. Several indicators of durable goods shipments are included to capture the flow of finished goods headed to manufacturers.

Industrial production indices are also included as measures of the real economy-wide output of manufacturing goods. Real equipment investment represents the broadest measure of output in the business equipment sector. Quarterly indicators of commercial and industrial charge-off rates, which track the financial health of the commercial and industrial financing sector, are included to test whether CFI financial data can improve forecasting for broader measures of financial health.

Data on durable goods orders and shipments come from the Census's Manufacturers' Shipments, Inventories, and Orders (M3). Industrial production data are pulled from the Federal Reserve's Industrial Production and Capacity Utilization (G.17) report. Gross Domestic Product data on real business investment comes from the Bureau of Economic Analysis's National Income and Product Accounts. Data on commercial and industrial loan performance come from the Federal Reserve's report on Charge-off and Delinquency Rates on Loans and Leases at Commercial Banks. All data are queried through the Federal Reserve Bank of St. Louis's FRED database, and all series codes are provided in Appendix C.

The monthly and quarterly data sets used in this analysis, for both the CFI and government indicators, contain data from January 2006 through April 2025.

Methodology and Evaluation

Nowcasting Versus Forecasting

Evaluating the predictive power of a data series requires establishing a statistical relationship between the data used for forecasting and the data being forecasted. For time series data, such as the CFI and most government statistics, the link is established by using previous values to predict future data. When the data being used to predict is only from previous data periods, the process is referred to as forecasting. However, in practice, data is released at different times and at various frequencies. Researchers can exploit those timing differences to predict data series that come out later in the same period. That process is called nowcasting, and it focuses on predicting at very short time horizons.[iii] This analysis examines the predictive power of CFI data for both nowcasting and forecasting government data releases.

Model Specification and Testing

To assess whether CFI data enhances the predictive power of standard forecast models, it is essential to first establish a set of standard forecast specifications for each government indicator. As noted above, a common forecasting technique is to use an indicator's own historical values to forecast future data. When a model uses only lags of the dependent variable (the variable being predicted) to forecast, it is called an autoregressive process, and each model specification is denoted by AR (number of lags in the model). So, a model that uses just last month to predict this month is an AR(1) model. A model that uses last month and two months ago is an AR(2) model. Our baseline forecast set includes three model specifications: an AR(1), an AR(2), and an AR(3) model specification for each government variable.

As is best practice in time series modeling, all data are transformed into either log differences, or differences for the rate variables, to remove time trend components (i.e., the fact that economic data tend to move in one direction, up or down, over time).

The standard approach to forecasting and nowcasting involves using a subset of historical data to train the model, while withholding some of the historical data to compare against the model-generated forecasts. One issue with this approach is that relationships and model results often vary over time. It is therefore essential to conduct robustness checks by testing the model specification against various forecast windows to determine if the results remain consistent across different forecast horizons. For this analysis, we've used withholding windows (the number of historical periods withheld from the model's training to evaluate forecast performance) for the last 12 months and last 24 months for the monthly variables, and the last 20 quarters for the quarterly tests. Expanding rolling windows, where the model forecasts one period ahead and then uses that information to improve the model for the next period, were also tested.

A measure of forecast error called the normalized root mean squared error (NRMSE) is calculated for each model. The NRMSEs for the traditional autoregressive models are then compared to the NRMSEs of the CFI models for each government statistic to assess whether including CFI data improves predictive performance. The lower the NRMSE, the lower the forecast error. Once the NRMSEs are calculated, a Diebold-Mariano test, implemented with Newey-West standard errors to account for serial correlation (Diebold & Mariano, 1995),[iv] determines whether improvements are statistically significant at the 5% level. To interpret the results, a "5.4% improvement" means the forecast error (NRMSE) decreased by 5.4%—for instance, from 1.00 to 0.946. This is not a 5.4 percentage point improvement in the forecast itself, but rather a proportional reduction in forecast error.

Empirical Results

Overview

This analysis tests 75 unique indicator-predictor combinations: 25 for nowcasting (where timing advantages exist) and 50 for forecasting (using only lagged data). These combinations span monthly manufacturing indicators and quarterly credit metrics, evaluated across multiple time windows. The results reveal 21 statistically significant improvements at the 5% level, substantially exceeding the four improvements that would be expected by chance alone.

Nowcasting Performance

Nowcasting analysis yields seven significant improvements across 25 valid tests, producing a 28.0% success rate. These improvements are entirely in topline durable goods orders and shipments in the Census's durable goods report, where the CFI data enjoy natural timing advantages.

As the nowcasting heat map in Appendix A shows, four CFI data series improved nowcasting of government data, with three improving the forecasts of more than one official measure. Durable goods orders demonstrated the most consistent nowcasting gains, with three different CFI predictors providing statistically significant improvements. Small ticket NBV delivers the highest average improvement at 3.8% error reduction when forecasting new orders of manufacturers' durable goods, excluding defense. Small ticket NBV also improved nowcasts of total new orders by an average of 3.1%, while captive NBV and total NBV reduced them by 1.5% and 0.8%, respectively. Small ticket NBV's strong nowcasting performance, particularly for new orders, stems from small businesses' greater exposure to economic cycles. These firms typically operate with limited financial buffers, making their equipment acquisition decisions highly responsive to current business conditions. The substantial improvement in forecasts of durable goods orders suggests that small business financing activity provides a particularly timely indicator of order momentum.

Manufacturing shipments show more modest gains, with bank NBV providing statistically significant but small improvements of 0.1% to 0.3% for both manufacturer and durable goods shipments.

Forecasting Performance

The forecasting evaluations reveal 14 significant improvements across 50 valid combinations, yielding a 28.0% success rate, which coincidentally matches the nowcasting rate. The forecast evaluations contained a larger set of government data, and the strength of the results strongly indicates that incorporating CFI data reduces forecast errors across a range of official data on equipment demand and production.

The forecasting heat map in Appendix A illustrates which CFI-incorporated models resulted in lower forecast errors. While six of the series improved forecasting for various economic indicators, the results were not uniform. Captive NBV reduced forecast errors for durable goods manufacturing shipments by 7.3% and total durable goods shipments by 7.0%—the largest improvements in the entire analysis. Small ticket NBV performed well across both categories, reducing errors by 4.3% and 4.7% for the same two series, respectively, while independent NBV contributed improvements of 2.8% and 3.2%. These substantial gains suggest that equipment financing decisions, particularly those made by captive companies with deep industry knowledge, are essential for enhancing economic forecasting of durable goods orders and shipments. Figure 2 in the Appendix A provides a comprehensive list of results.

The Importance of Timing

A direct comparison of nowcasting and forecasting results shows the importance of releasing the CFI before the durable goods report every month. The maximum timing advantage—the additional improvement from using contemporaneous (nowcasting) rather than lagged data (forecasting)—for predicting total durable goods orders was 2.4 percentage points (3.1% average error reduction in the nowcasting models minus 0.7% in the forecasting models).

Statistical Considerations

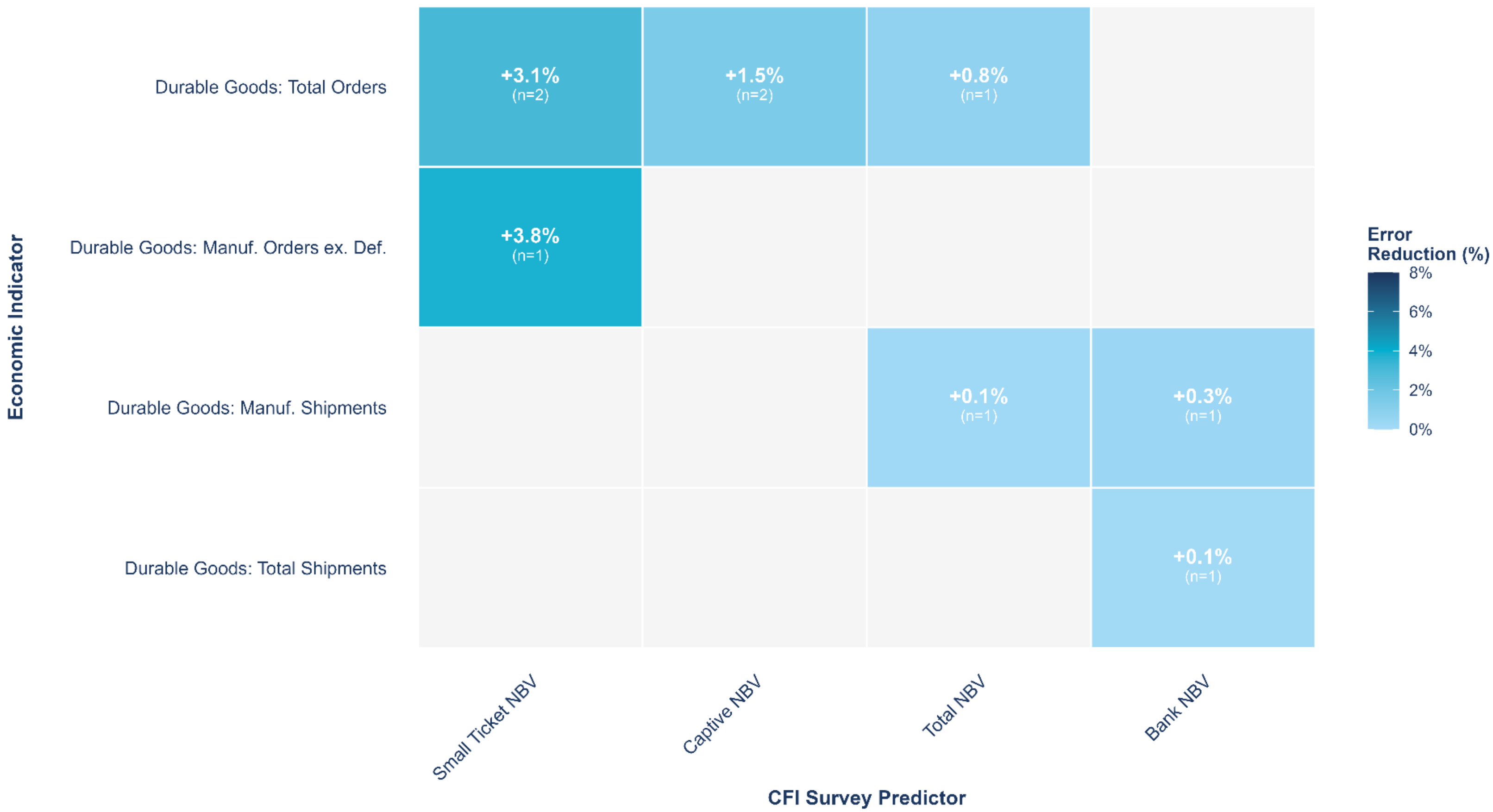
Several caveats qualify the results. First, 75 indicator-predictor-window combinations were tested at the 5% significance level. By chance alone, approximately four false positive results would be expected. The analysis identified 21 significant improvements in total—seven for nowcasting and 14 for forecasting—indicating that the reduction in forecast error from including CFI data is more than mere chance.

Second, these reported improvement percentages are conditional on statistical significance. The average improvements we cite—such as 7.3% error reduction for forecasts of manufacturing shipments—represent the mean among statistically significant results only. The unconditional expected improvement across all possible applications would be considerably lower, as it would include the many combinations that showed no significant improvement.

Appendix A: Heat Maps

Figure 1. CFI Survey Data Improves Economic Nowcasting

Average Forecast Error Reduction



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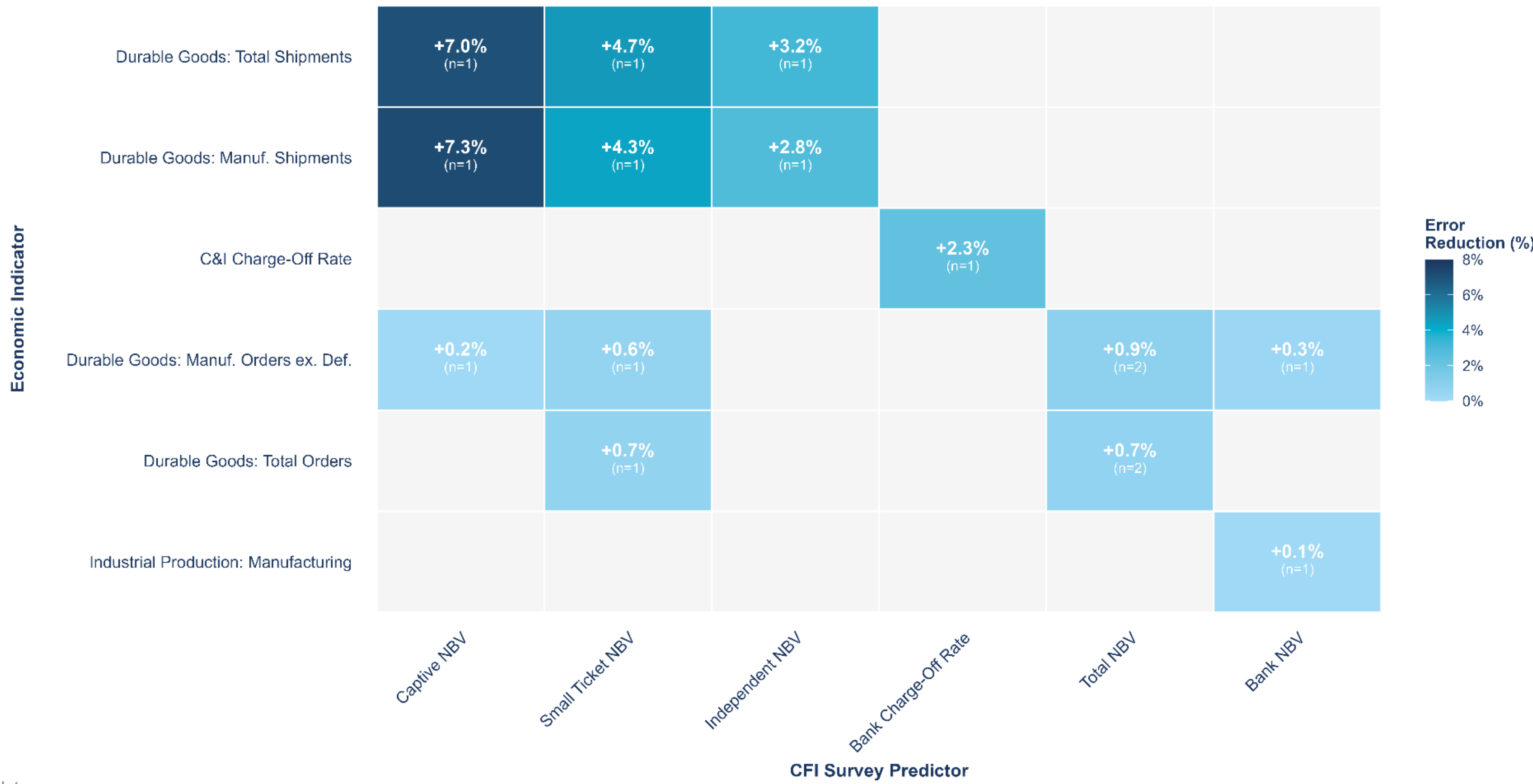
Source: ELFA CapEx Finance Index and Federal Reserve Economic Data (FRED)

Figure 2. CFI Survey Data Improves Economic Forecasting

Average Forecast Error Reduction



Notes:

(1) Only indicator-predictor pairs with significant improvements are shown. Gray cells were tested but not significant at the 5% level.
(2) n = the number of significant forecast windows.
(3) Forecasting uses only historical data (lagged CFI and economic indicators) for true out-of-sample prediction.

Source: ELFA CapEx Finance Index and Federal Reserve Economic Data (FRED)

Appendix B: Error Reduction Ranges

Table 1. CFI Data Improves Economic Analysis: Summary of Significant Results

Economic Indicator	Analysis Type	Range of Improvement	N Tests	Best Predictor
Durable Goods: Manuf. Shipments	*Nowcast*	0.1% - 0.3%	2	Bank NBV
	Forecast	2.8% - 7.3%	3	Captive NBV
Durable Goods: Total Shipments	*Nowcast*	0.1%	1	Bank NBV
	Forecast	3.2% - 7.0%	3	Captive NBV
Durable Goods: Total Orders	*Nowcast*	0.5% - 5.4%	5	Small Ticket NBV
	Forecast	0.2% - 1.3%	3	Total NBV
Durable Goods: Manuf. Orders ex. Def.	*Nowcast*	3.8%	1	Small Ticket NBV
	Forecast	0.2% - 1.3%	5	Total NBV
C&I Charge-Off Rate	*Forecast*	2.3%	1	Bank Charge-Off Rate
Industrial Production: Manufacturing	*Forecast*	0.1%	1	Bank NBV

Summary Statistics:

Simple average improvement: 1.6% (nowcast) vs 2.3% (forecast)

Weighted average improvement: 1.6% (nowcast) vs 2.3% (forecast)

Note: Simple average treats each significant result equally. Weighted average accounts for the number of significant tests per indicator.

Indicators with >5% improvement: 3 of 6

Note: All improvements shown are statistically significant ($p<0.05$). Improvements represent the reduction in forecast error (NRMSE) when CFI data is added to autoregressive models. Results shown are conditional on achieving statistical significance; the unconditional expected improvement across all tests would be lower.

Appendix C: Government Indicator Codes

Table 2. FRED Database Series Indicators

Economic Indicator	FRED Code	Frequency
Durable Goods: Total Orders	DGORDER	Monthly
Industrial Production: Business Equipment	IPBUSEQ	Monthly
Industrial Production: Manufacturing	IPMAN	Monthly
Manufacturers' New Orders: Durable Goods Excluding Defense	ADXDNO	Monthly
Manufacturers' New Orders: Nondefense Capital Goods Excluding Aircraft	NEWORDER	Monthly
Shipments: Manufacturers	AMDMVS	Monthly
Shipments: Total Durable Goods	ADXDVS	Monthly
C&I Charge-Off Rate	CORBLACBS	Quarterly
Delinquency Rate: Business Loans	DRBLACBS	Quarterly
Real Equipment Investment	Y033RC1Q027SBEA	Quarterly

Source: Federal Reserve Economic Data (FRED), Federal Reserve Bank of St. Louis
Note: Monthly indicators are available for both nowcasting and forecasting analysis. Quarterly indicators are used for forecasting analysis only.

About the Author

Tim Mahedy is the CEO and Chief Economist of Access/Macro, a consulting company and data analytics provider for financial institutions, industry organizations, and institutional investors. Tim is a former Fed forecaster and chief of staff to the President and CEO of the Federal Reserve Bank of San Francisco. He previously worked at the International Monetary Fund and on Wall Street.

Access/Macro provides companies with world-class economic research and forecasting, develops enterprise data architectures and custom analytical solutions, and writes tailored research reports.

Endnotes

[i] Equipment Leasing &Finance Foundation. Horizon Report 2024, 10/28/2024. https://www.leasefoundation.org/industry-research/horizon-report/.

[ii] The equipment finance industry represents 4.83% of the U.S. economy. That number was arrived at by dividing the estimated size of the industry in 2023, $1.34 trillion, from the Horizon Report 2024 (citation above), by 2023 nominal GDP from the Bureau of Economic Analysis, which was $27.7207 trillion.

[iii] Bańbura, M., Giannone, D., Modugno, M., & Reichlin, L. (2013). Now-casting and the real-time data flow. In G. Elliott & A. Timmermann (Eds.), *Handbook of Economic Forecasting* (Vol. 2, pp. 195-237). Elsevier.

[iv] Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics*, 13(3), 253-263.