TENDER ALPHA

GOVERNMENT CONTRACTS DATA AND STOCK PRICE MOVEMENTS – SIGNAL TESTING

Forward-Looking Receivables from US Federal Contracting and Relationship with Stock Price Movements of Government Suppliers

NOV 2020

CONTENTS

EXECUTIVE SUMMARY

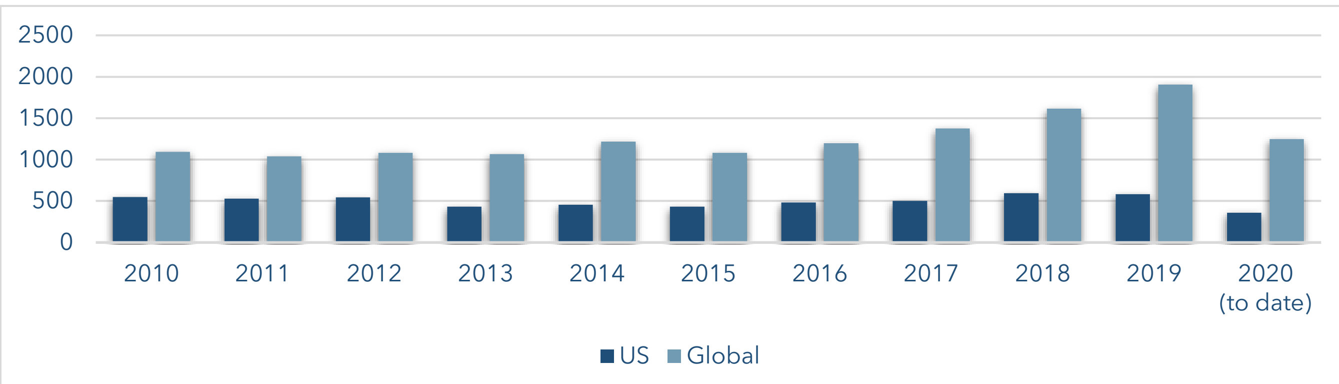
KEY POINTS

Global government contracting data by TenderAlpha.com (a product of BizPortal.co) accounts for nearly **USD 15 trillion of government spending since 2010** of which nearly USD 6 billion made by US Federal Government (Figure 1).

With a focus on US federal contracting, we show that information about government contracts awards is not immediately incorporated into stock prices and can be used to construct signals for predicting cross-sectional stocks returns for major suppliers to US government.

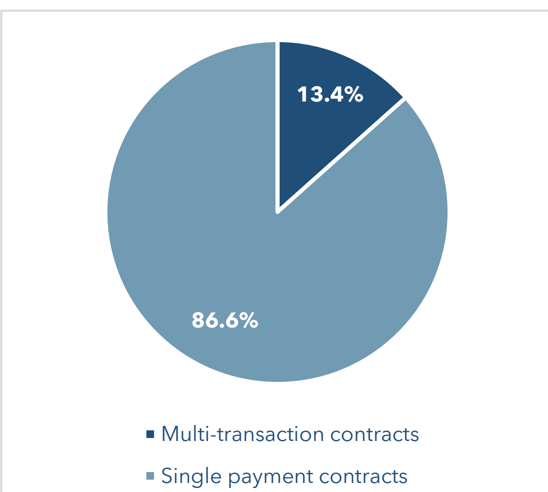
Although much smaller in terms of number of contracts (Figure 2), multi-transaction contracts account for more than 85% of the total USD value of US federal contracts (or nearly **USD 5 trillion from 2010 to today**) thus allowing accurate receivables projections per ticker (Figure 3).

Figure 1. Global vs. US Federal Aggregate Contract Awards Value (2010-2020) (USD bn)



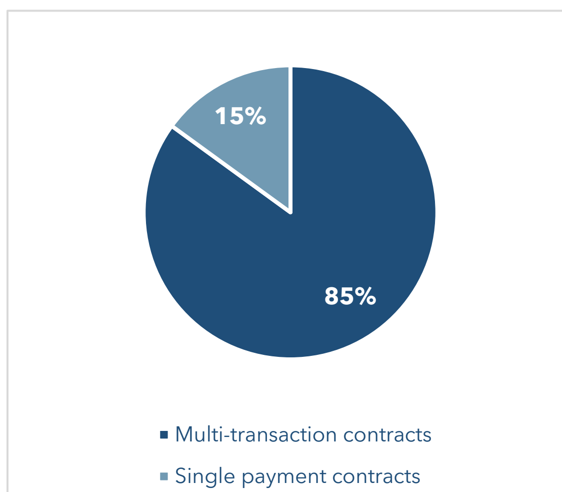
Source: TenderAlpha.com

Figure 2. Multiple Transaction vs. Single Payment US Federal Contracts (Number of Contracts Distribution) (%)



Source: TenderAlpha.com

Figure 3. Multiple Transaction vs. Single Payment US Federal Contracts (Distribution in terms of USD Value) (%)



Source: TenderAlpha.com

METHODOLOGY

We utilize the database of forward-looking receivables between 2013 and 2019 derived from the information of payment cycle of each US federal contract and backtest multiple trading strategies that go long on firms with government receivables and short the rest of the market with variations of the weighting of stocks in the portfolios and the universe in which they are implemented

To tease out the effect of new contract awards (surprise/additional government receivables) outside the receivables from already awarded contracts, **we create an unexpected government receivables (UGR) signal.**

We backtest the strategies using the following steps:

1 We scale the forward-looking government receivables for each stock at the end of each month by the stock's market capitalization.

2 We extract the unexpected component of receivables by subtracting the average forward-looking receivables for each firm over the past year and dividing by their standard deviation over the same period.

3 We test the performance of our strategies by calculating their Sharpe ratios and estimating alphas with respect to various factor models controlling for market, size, value, momentum, profitability, and investment equity factors.

RESULTS

In all cases, the strategies perform extremely well and achieve annualized Sharpe ratios between 0.77 and 1.27, a range that spans between double and just over triple the historical Sharpe ratio of the market portfolio of 0.35-0.40.

The strategies' **alphas are in all cases significant and range between 3.4% and 7.1% per year** depending on the strategy and the factor model used as follows:

- A trading strategy that goes long in stocks that are in the highest tercile of UGR and short stocks with no government receivables, and equally weights stocks within the long and short portfolios, achieves an annualized Sharpe ratio of 1.27. Its alpha ranges from 5.4% to 7.1% per year depending on the factor model used and is highly statistically significantly different from zero.
- A more easily implementable market-cap-weighted version of this trading strategy achieves an annualized Sharpe ratio of 0.82, with alphas ranging from 4.3% to 4.6% per year.
- To further account for the ease of implementation, a version of the market-cap-weighted UGR trading strategy implemented only among the Russell 1,000 universe achieves an almost indistinguishable performance relative to same strategy implemented in the full universe of publicly traded stocks noted above.
- Finally, we also backtest strategy that is trivial to implement - one that goes long a market-cap-weighted portfolio of about 100 stocks on average that are in the top tercile of UGR among Russell 1,000 stocks, and shorts the total market (e.g., a market ETF). This strategy yields an annualized Sharpe ratio of 0.77, and its alphas range from 3.4% to 4.1% per year.

A version of this strategy in which the signal is updated daily instead of monthly achieves similar performance. Moreover, **the results seem to be long-lasting** – it takes up to seven months until the alpha becomes insignificant.

RESEARCH SCOPE AND LIMITATIONS

Our sample includes ordinary common stocks for roughly 3,800 stocks traded on the NYSE, AMEX, and NASDAQ exchanges. We use receivables from US federal government contracts aggregated per ticker.

We find evidence that standardized scaled government receivables are a strong predictor of returns. This evidence is consistent with an extensive academic literature in behavioral finance on slow diffusion of information into stock prices. Nevertheless, further research is needed and the portfolio sorts presented in this document are limited. We have not yet looked into the inter- and intra-industry differences in government receivables and at benchmarking the receivables relative to the industry which could also result in more meaningful strategies.

INTRODUCTION

Public procurement is a term used to describe the purchasing of works, supplies and services on behalf of a public authority, such as a government agency, local (municipal) bodies, and public institutions such as schools or hospitals. With nearly 20% of GDP worldwide accounting for government spending, public procurement is a substantial part of the global economy.

Government procurement has a significant impact on the private sector as it reduces the risk for firms supplying government agencies. Firms with government agencies as major customers tend to have lower cash flow uncertainty due to the virtually risk-free nature of government receivables. Specifically, Huang et al. (2016) state that having the government as a major customer substantially reduces the contractor's cash flow risk, financial distress risk, and the need for excess cash holdings. Paglia and Harjoto (2014) posit that stable government cash flows help firms with government contracts to secure private equity or venture capital funding. Similarly, Dhaliwal et al. (2016) state that government customers are less likely to default and less likely to switch suppliers; correspondingly, they find that government contractors have a lower cost of equity.

In this study we find strong evidence that information about a firm's receivables from U.S. Federal government contract awards can be used to predict the firm's stock returns. We construct and backtest trading strategies using signals from a government contracts receivables database in the universe of all publicly traded stocks in the U.S. We find that our trading strategies can generate excess returns in the backtests and cannot be explained by exposure to common factors in the cross-section of stock returns.

We construct the signals on which we sort stocks in our trading strategies using a database product offering by TenderAlpha. The product consists of aggregated government procurement contract awards and related company information. The product monitors daily USD value of government purchasing per country and globally through its indexing solutions providing daily delivery options with 10+ years of contracts data history. It provides above 70 million awarded contracts accounting for approximately USD 15 trillion global government spending distributed to over 2 million unique companies with full project information in a structured, cleaned and aggregated data format. Nearly 40% of the USD 15 trillion is awarded to publicly listed companies. The data is ticker-mapped and point-in-time thus allowing signal testing and analysis.

For the purposes of the current study, we focus on US federal government contracting as the structure of US public procurement provides the option for deriving accurate receivables projections per contract and the option for aggregation per ticker.

MOTIVATION

An extensive academic literature in behavioral finance suggests that equity investors have limited attention and do not immediately incorporate all publicly available information into stock prices. Researchers have documented hundreds of patterns in the cross-section of U.S. stock returns (Harvey, Liu, and Zhu, 2016) termed anomalies because they produce trading strategies that have significant average returns, even after controlling for exposure to standard risk factors.

A significant number of these anomalies are often attributed to limited investor attention.

For example, Ball and Brown (1968) are the first to show that stock prices tend to drift in the direction of the announced quarterly earnings, a phenomenon known as the post-earnings announcement drift (PEAD). More recently, Richardson, Tuna, and Wysocki (2010) survey anomalies that derive from an underreaction to publicly available accounting information.

Similarly, information that requires a greater cognitive burden is even harder to incorporate quickly. For example, Cohen and Frazzini (2008) show that a firm's stock price adjusts slowly to important economic news about the firm's major customers. Similarly, Cohen and Lou (2012) show that economically relevant industry-specific information is incorporated more quickly into firms operating in a single industry as opposed to into conglomerates.

A host of other papers document slow diffusion of information into stock prices in various other settings (an incomplete list includes, e.g., Lo and MacKinlay, 1990; Hou, 2007; Cohen, Diether, and Malloy, 2007; Menzly and Ozbas, 2010; Cohen, Malloy, and Pomorski, 2012; Cohen, Diether, and Malloy, 2013; Korniotis and Kumar, 2013; Parsons, Sulaeman, and Titman, 2017; etc.)

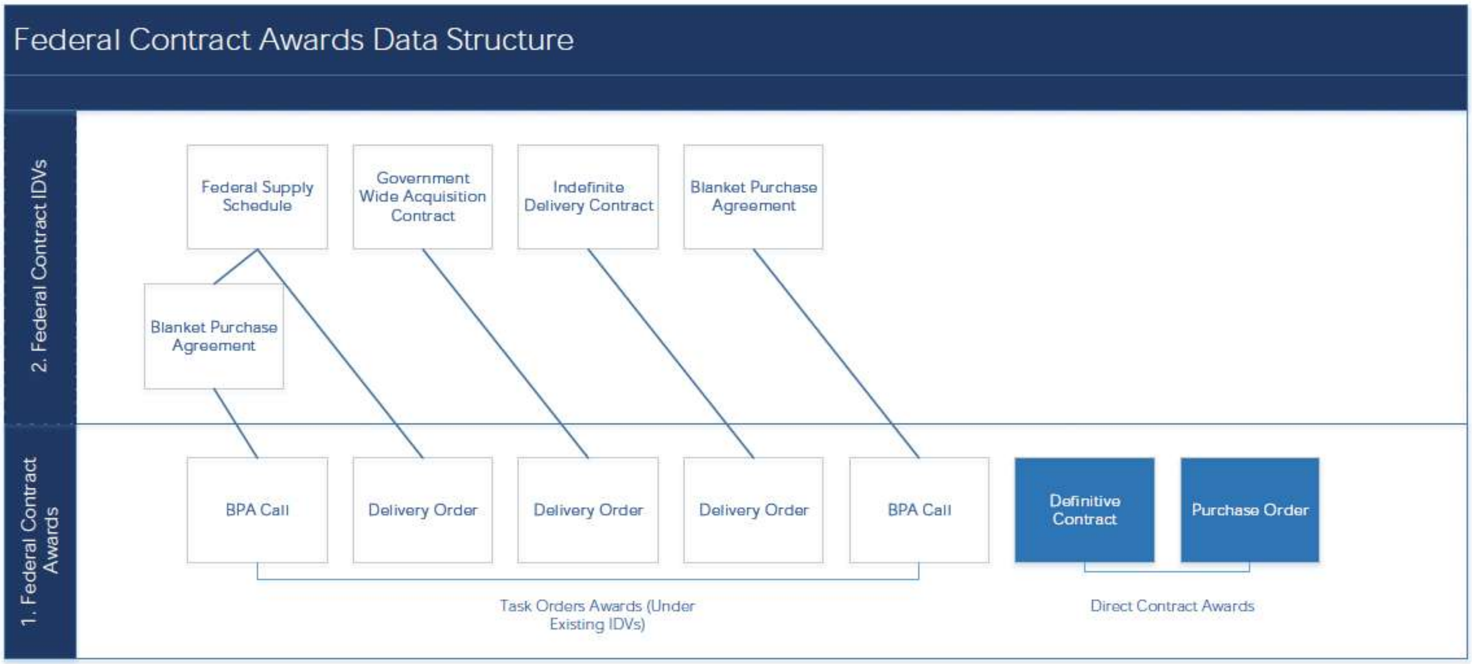
Government procurement data, while publicly available, is difficult to process. Thus, we hypothesize that investors are slow to incorporate this information, consistent with the studies noted above. This hypothesis is consistent with the literature that finds that government procurement has a significant impact on the private sector as it reduces the risk for firms supplying government agencies.

Exposure to government contract awards may also result in higher cash flows, as government contractors have been found to have higher profitability and better operating performance (Lichtenberg, 1992; McGowan and Vendrzyk, 2002; Ngo, 2010). Belo et al. (2013) measure different industries' exposure to government expenditure, finding that, during the terms of Democratic (Republican) presidents, firms in industries with high government exposure significantly outperform (underperform) firms in industries with low government exposure.

FORWARD-LOOKING RECEIVABLES FROM GOVERNMENT CONTRACTS

Our main hypothesis is that it is very costly for investors to process the information regarding government procurement contract awards sufficiently quickly. While the biggest contracts catch the attention of media outlets, the vast majority of contract awards do not receive any press coverage. To test our hypothesis, however, we need reliable data on government procurement. TenderAlpha provides a pipeline with the exact budget execution percentage of government contracts receivables. This allows us to calculate the future receivables of each contract. Having available the full payment history throughout the contract, we provide all receivables of all future contracts and/or receivables for next 12 months/3 months/ any given point in the future. The hierarchical organization of the United States Federal Public Procurement System consists of two main levels: Indefinite Delivery Vehicle Level and Contract Awards Level (Exhibit 1). Contract awards represent different types of definitive delivery procurement instruments (i.e. the immediate requirement is known and awarded with all the attendant terms and conditions). The bottom level of the contract data hierarchy is where public funds are obligated. Each contract award is comprised of a number of transactions. Each transaction represents funds transfer from the funding agency to the awarded vendor. The sum of all transactions' values shows how much public

Exhibit 1: Federal Contract Awards Data Structure



Source: TenderAlpha.com

funds have been obligated to a vendor compared to the initial indicative value of the contract award at any point in time.

Making forward projections requires numerous inputs. The reliability and accuracy of the data drive the forecasts. In the context of the USD receivables from government contracting – each public company's receivables upon each multi-transaction contract award made by the Federal Government in the US could be modeled very accurately. At any point of time, TenderAlpha's data could show how much Ticker X ought to receive in the next few years under Contract Y if Contract Y's potential contract value is larger than the current event amount and then it is expected to be materialized in multiple transactions over the next few years defined by the contract's end date. When all multi-transaction contracts of Company X and its subsidiaries are aggregated per ticker, the investors could then analyze on dynamic basis (as a point in time) the government sales pipeline thus allowing for very powerful forecasts.

Approximately 90% of the total USD value of US federal contracts (or nearly USD 5 trillion from 2010 to today) is awarded through multi-payment contracts thus allowing accurate receivables projections per ticker. They represent only 15% of in terms of contracts (the remaining vast majority are single-payment contract) which demonstrates that major US federal contracts always consist of multiple payments.

TESTING FRAMEWORK

To test our hypothesis, we need to examine whether the information contained in government contract awards is relevant for stock return predictability. To this end, we utilize the database on forward-looking pipeline of receivables from government contracts provided by TenderAlpha and design and backtest multiple trading strategies in the cross-section of equity returns.

We begin by merging the government contracting data provided by TenderAlpha into a dataset containing stock returns for the entire universe of ordinary common shares traded on major U.S. exchanges (NYSE, NASDAQ, AMEX). Out of the 9.3 million raw observations provided by TenderAlpha, roughly 3.4 million were dropped due to missing data. Restricting the data to U.S. listed stocks and ending the sample in 2019, another 3.1 million observations were dropped, resulting in 2.8 million stock-day observations on forward-looking receivables from government contracts (Figure 9 – Appendix)

As a first pass, we examine monthly portfolio returns, so for each stock-month, we leave only the last available daily observation. The restriction leaves roughly 95 thousand stock-month observations. We match these observations to our monthly stock return data using ticker and exchange name provided by TenderAlpha. The final sample includes roughly 86 thousand stock-month observations spanning 2012 to 2019.

All trading strategies we examine will be backtested using a standard academic portfolio construction. That is, we construct the strategies by sorting stocks based on a candidate signal at the end of each month, and forming long/short self-financing portfolios that go long stocks with high predicted returns and short stocks with low predicted returns. The stocks are held for a month, at which point the portfolios are rebalanced. Stock returns within each portfolio are equally- or value-weighted (i.e., the weight of each stock is proportional to its market capitalization, relative to the market capitalization of the entire portfolio).

The backtested strategies are evaluated based on several criteria. First, we look at the average monthly returns for the strategies, and the associated t-statistic. We also study the strategy's Sharpe ratio and plot and visually inspect the returns for the strategies over the entire sample, for each calendar year, and on a five-year rolling basis.

Apart from the raw returns of the trading strategies, we also evaluate the risk-adjusted performance (alpha) of the strategies controlling for market, size, value, profitability, investment, and momentum factors. We use the standard long/short academic factor constructions of the Fama and French (1993; 2015; 2018) factor models and estimate the alphas from time-series regressions of the returns to our strategies on the factor returns. These regressions help us assess the drivers of portfolio returns and ensure that we are not capturing exposure to standard and well-known risk factors.

The factor models and associated regression equations we estimate are as follows:

- Standard CAPM model:
$$r_{it} = \alpha_i + \beta_{MKT} \times r^e_{MKT} + \varepsilon_{it}$$

- Fama and French (1993) three-factor model:
$$\begin{aligned} r_{it} = \alpha_i + \beta_{MKT} \times r^e_{MKT} + \beta_{SMB} \times r_{SMB} \\ + \beta_{HML} \times r_{HML} + \varepsilon_{it} \end{aligned}$$

- Carhart (1997) four-factor model:
$$\begin{aligned} r_{it} = \alpha_i + \beta_{MKT} \times r^e_{MKT} + \beta_{SMB} \times r_{SMB} \\ + \beta_{HML} \times r_{HML} \\ + \beta_{UMD} \times r_{UMD} + \varepsilon_{it} \end{aligned}$$

- Fama and French (2015) five-factor model:
$$\begin{aligned} r_{it} = \alpha_i + \beta_{MKT} \times r^e_{MKT} + \beta_{SMB} \times r_{SMB} \\ + \beta_{HML} \times r_{HML} \\ + \beta_{RMW} \times r_{RMW} \\ + \beta_{CMA} \times r_{CMA} + \varepsilon_{it} \end{aligned}$$

- Fama and French (2018) six-factor model:
$$\begin{aligned} r_{it} = \alpha_i + \beta_{MKT} \times r^e_{MKT} + \beta_{SMB} \times r_{SMB} \\ + \beta_{HML} \times r_{HML} \\ + \beta_{RMW} \times r_{RMW} \\ + \beta_{CMA} \times r_{CMA} \\ + \beta_{UMD} \times r_{UMD} + \varepsilon_{it} \end{aligned}$$

where the factors and associated loadings are defined as follows:

- r^{e}_{MKT} - returns to the market factor, calculated as excess return over the risk-free rate on the market portfolio
- β_{MKT} - loading on the market factor
- r_{SMB} - returns to the size factor, calculated as a portfolio that is long stocks small cap and short large cap stocks
- β_{SMB} - loading on the size factor
- r_{HML} - returns to the value factor, calculated as a portfolio that goes long stocks with high book-to-market values and short stocks with low book-to-market values
- β_{HML}- loading on the value factor
- r_{RMW} - returns to the profitability factor, calculated as a portfolio that is long stocks with robust (i.e., high) profitability and short stocks with weak (i.e., low) profitability
- β_{RMW} - loading on the profitability factor
- r_{CMA} - returns to the investment factor, calculated as a portfolio that goes long stocks with conservative (i.e., low) investment and short stocks with aggressive (i.e., high) investment
- β_{CMA}- loading on the investment factor
- r_{UMD} - returns to the momentum factor, calculated as a portfolio that goes long stocks with high past performance and short stocks with low past performance.
- β_{UMD}- loading on the momentum factor

All factor returns were downloaded from Professor Ken French's data library.

BACKTESTING RESULTS

An initial look of returns to stocks with government receivables

Our main hypothesis states that investors are slow to incorporate information about government receivables. Thus, to test this hypothesis, we need a signal that captures the additional information that is publicly available but difficult to process in government receivables. Before we get there, however, in this section we take a first pass at inspecting the returns to stocks with positive government receivables compared to the rest of the market.

Table 1. Backtest results for firms with and without government receivables

This table shows backtesting results of a simple trading strategy that goes long stocks with positive forward-looking government receivables and short stocks with no government receivables. The table reports average returns (r) and alphas on five different factor models (α's) in Panel A, and factor loadings on the factors in the Fama and French (2018) six-factor model (β's) in Panel B, for portfolios formed based on their forward-looking government receivables variable (usd_value_all), **GR**, and defined as follows:

- Portfolio (1) is firms with **GR** = 0 or **GR = N/A**
- Portfolio (2) is firms with **GR** > 0
- Portfolio (2)-(1) is a portfolio that goes long stocks in Portfolio (2) and short stocks in Portfolio (1)

Stocks are value-weighted within portfolios and the portfolio holdings are rebalanced at the end of each month. T-statistics are reported in brackets. The sample includes all U.S. publicly traded ordinary common shares of stock and the period is from January 2013 – December 2019.

Panel A: Excess returns and alphas from factor models (%/month)						
Portfolio	r	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	1.05	-0.09	-0.05	-0.04	-0.05	-0.04
	[3.01]	[-1.88]	[-1.17]	[-0.98]	[-1.15]	[-0.91]
(2)	1.21	0.12	0.07	0.06	0.06	0.05
	[3.62]	[1.91]	[1.22]	[1.09]	[1.18]	[0.98]
(2)-(1)	0.16	0.22	0.12	0.10	0.11	0.09
	[1.48]	[1.90]	[1.20]	[1.05]	[1.18]	[0.96]
Panel B: Loadings on Fama and French (2018) six-factor model						
Portfolio	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{UMD}
(1)	0.99	0.09	-0.01	-0.09	0.03	-0.02
	[73.11]	[4.51]	[-0.24]	[-2.92]	[0.81]	[-1.04]
(2)	1.00	-0.11	0.00	0.12	-0.03	0.02
	[55.87]	[-4.39]	[0.15]	[3.06]	[-0.61]	[0.79]
(2)-(1)	0.01	-0.20	0.01	0.21	-0.06	0.03
	[0.36]	[-4.46]	[0.19]	[3.01]	[-0.70]	[0.90]

Table 1 reports backtesting results of a simple trading strategy that goes long stocks with positive forward-looking government receivables and short stocks with no government receivables. We can observe that the long/short trading strategy achieves an average monthly return of 16 basis points per month, with alphas ranging from 9 to 22 basis points per month. While the CAPM alpha is statistically significantly different from zero, the rest of performance metrics indicate at best a marginal significance. We interpret this evidence as only suggestive of the power of forward-looking government receivables to predict returns. This is by far the simplest strategy one can design to trade on this information and we still see some marginally significant results in the backtest. More cleverly designed signals, such as the ones backtested in the following sections, can prove to be much more potent predictors of returns in the cross-section of equities.

"Unexpected government receivables" (UGR) signal construction details

To arrive at a signal that captures the new information that is publicly available but difficult to process by investors in government receivables, we develop a measure we term "unexpected government receivables" (**UGR**). The measure is calculated using the following steps:

1. At the end of each month *t*, for each stock *i*, we scale the forward-looking government receivables (**GR**) by the stock's market capitalization and arrive at the "scaled government receivables":

$$SGR_{it} = \frac{GR_{it}}{MarketCap_{it}}$$

2. The "unexpected government receivables" (**UGR**) are the "normalized" scaled government receivables (**SGR**), where the normalization is done by subtracting the average **SGR** over the previous year ($\mu_{SGR_{t-12,t-1}}$) and dividing by the standard deviation of **SGR** over the previous year ($\sigma_{SGR_{(t-12,t-1)}}$):

$$UGR_{it} = \frac{SGR_{it} - \mu_{SGR_{(t-12,t-1)}}}{\sigma_{SGR_{(t-12,t-1)}}}$$

The basic intuition behind the **UGR** measure is that investors should not be surprised about firms which consistently receive government contract awards or from a new contract awarded to a traditional supplier to the federal government that is not material compared to the usual USD size of contracts awarded to the same company. A high value of **UGR** indicates that a firm's forward-looking receivables have significantly increased over the past month relative to their average value over the past year, accounting for the variation in the receivables using the standard deviation in the denominator. We hypothesize that these are precisely the stocks for which it is difficult for investors to parse the information for new public contract announcements especially in the context of aggregation of all already contracted US federal future deliveries. Based on domain public procurement knowledge and real-time/point-in-time monitoring of both the execution of existing contracts and the announcements of new federal contracts, the forward-looking receivables data offers a few steps of aggregation which is not available through any raw information from the institutional/media/company announcements. It is specifically designed to leverage the UGR effect as compared to value of expected receivables (and thus size of existing business with the federal government) at any point in time and over any given period of time.

Backtesting an equal-weighted "unexpected government receivables" (UGR) strategy

To test our hypothesis, **Table 2** shows backtesting results for a trading strategy that goes long stocks with high unexpected government receivables and short stocks with no government receivables. In this table, we report results for strategies which equally weight returns on stocks within the portfolios.

Table 2. Backtest results for equally-weighted UGR trading strategy

This table shows backtesting results for a trading strategy that goes long stocks with high unexpected government receivables and short stocks with no government receivables. The table reports average returns (r) and alphas on five different factor models (α's) in Panel A, and factor loadings on the factors in the Fama and French (2018) six-factor model (β's) in Panel B, for portfolios formed based on their unexpected government receivables variable, **UGR**, and defined as follows:

- Portfolio (1) is firms with **GR** = 0 or **GR = N/A**
- Portfolio (2) is firms with **UGR** in bottom tercile
- Portfolio (3) is firms with **UGR** in middle tercile
- Portfolio (4) is firms with **UGR** in top tercile
- Portfolio (4)-(1) is a portfolio that goes long stocks in Portfolio (4) and short stocks in Portfolio (1)

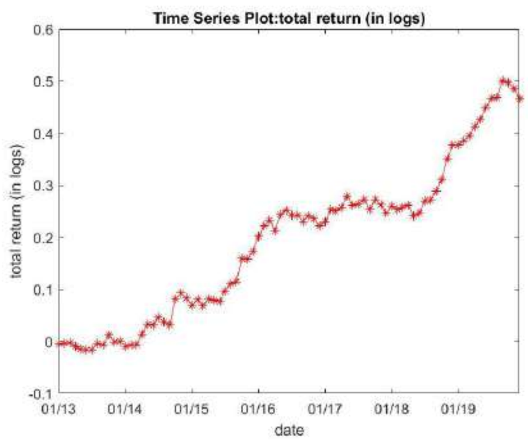
Stocks are equal-weighted within portfolios and the portfolio holdings are rebalanced at the end of each month. T-statistics are reported in brackets. The sample includes all U.S. publicly traded ordinary common shares of stock and the period is from January 2013 – December 2019.

Panel A: Excess returns and alphas from factor models (%/month)						
Portfolio	r	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.81	-0.54	-0.19	-0.13	-0.16	-0.09
	[1.62]	[-2.07]	[-1.41]	[-1.03]	[-1.26]	[-0.74]
(2)	1.14	0.02	0.19	0.17	0.19	0.16
	[2.95]	[0.13]	[2.02]	[1.81]	[2.02]	[1.76]
(3)	1.00	-0.26	-0.02	-0.01	-0.01	-0.01
	[2.25]	[-1.39]	[-0.15]	[-0.11]	[-0.11]	[-0.08]
(4)	1.37	0.05	0.28	0.37	0.29	0.39
	[2.95]	[0.25]	[1.99]	[2.91]	[2.00]	[3.00]
(4)-(1)	0.57	0.59	0.48	0.50	0.45	0.48
	[3.38]	[3.32]	[2.92]	[3.07]	[2.81]	[2.92]
Panel B: Loadings on Fama and French (2018) six-factor model						
Portfolio	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{UMD}
(1)	0.94	0.73	-0.00	-0.35	-0.03	-0.18
	[24.74]	[13.03]	[-0.01]	[-3.91]	[-0.25]	[-4.12]
(2)	0.92	0.46	-0.07	-0.04	0.17	0.06
	[30.66]	[10.48]	[-1.40]	[-0.54]	[2.15]	[1.73]
(3)	0.97	0.59	0.02	-0.03	0.08	-0.01
	[28.87]	[12.01]	[0.27]	[-0.42]	[0.84]	[-0.21]
(4)	0.98	0.46	-0.06	-0.17	0.03	-0.23
	[23.66]	[7.57]	[-0.79]	[-1.72]	[0.28]	[-4.97]
(4)-(1)	0.04	-0.27	-0.06	0.18	0.06	-0.06
	[0.70]	[-3.50]	[-0.62]	[1.49]	[0.40]	[-0.93]

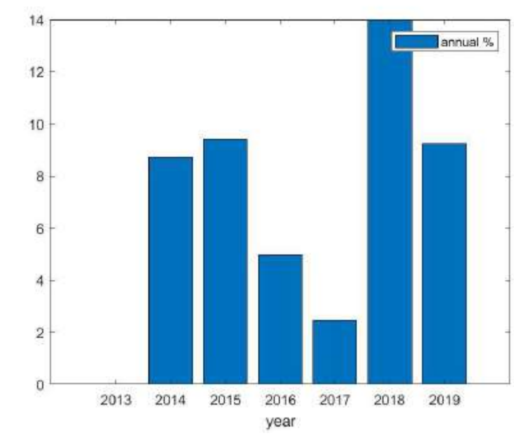
We can observe that the strategy performs extremely well in the backtest. The average returns to the long/short portfolio, reported in the last row of Panel A, are 57 basis points per month, with a t-statistic of 3.38. This result indicates that the average monthly returns to this strategy are both economically and statistically highly significant. The annualized Sharpe ratio of the strategy equals 1.28, which is more than three times the market's long-run historical Sharpe ratio of 0.35-0.40.

Similarly, the strategy alphas range between 45 and 59 basis points per month, depending on the factor model employed, and all of them are statistically significantly different from zero. The loadings on the six-factor model, presented in Panel B, show that the strategy does not proxy for any of the commonly used risk factors in the cross-section of stock returns. The positive and highly significant loadings on the SMB factor for portfolios (1) – (4) reflect the equal-weighted construction of the portfolio returns.

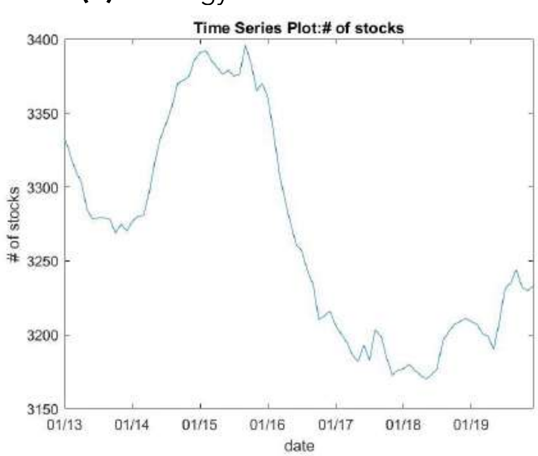
Figure 4. Backtest results for equally-weighted UGR trading strategy

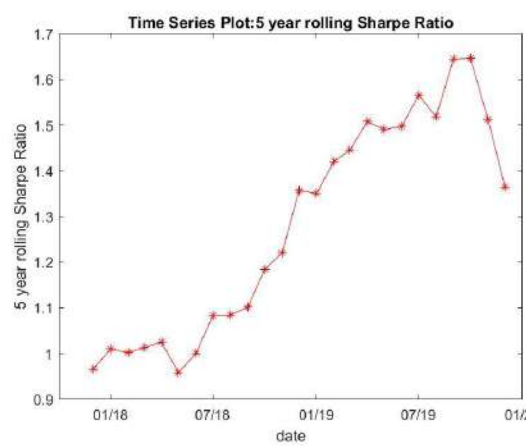


(a) Strategy cumulative return



(b) Strategy performance by year





(c) Combined # of stocks in long and short portfolios

(d) Strategy rolling 5-year Sharpe ratio

Figure 4 further documents the performance of the **UGR** trading strategy over the 2013-2019 sample used in our backtest. Panel (a) shows the cumulative return to the long/short strategy, panel (b) shows the annual return in each full year in our sample, panel (c) reports the number of stocks held in the long and short portfolios, and panel (d) shows the rolling 5-year Sharpe ratio of the trading strategy.

We can observe that the strategy performs remarkably well throughout the entire sample. The only year in which the strategy did not perform well was 2013, when its annual return was effectively 0% (which is why it is not visible on the graph).

Backtesting a market-cap-weighted "unexpected government receivables" (UGR) strategy

The equally-weighted **UGR** strategy presented in the previous section, while having an impressive paper backtested performance, is difficult to implement because it requires taking a short position in a large number of stocks that comprise the short leg of the long/short portfolio. Moreover, putting the same weight on all stocks within the long and short portfolios and using the entire cross-section of publicly traded firms means that the strategy takes short position in some very small stocks that are prohibitively costly to short.

To alleviate this concern, Table 3 shows backtesting results for a similar trading strategy that goes long stocks with high unexpected government receivables and short stocks with no government receivables. In this table, however, we report results for strategies which weight returns on stocks within the portfolios based on their market capitalization. Thus, tiny stocks would receive a very small weight in the portfolio relative to stocks, say, in the S&P 500.

We can observe that the market-cap weighted long/short strategy in Table 3 also exhibits an impressive performance. It yields 35 basis points per month, with a significant t-statistic of 2.19. Its annualized Sharpe ratio for the full backtested sample equals 0.82, a number more than double the long-run historical Sharpe ratio of the market portfolio of 0.35-0.40.

The returns to the strategy also do not seem to be spanned by any of the five factor models we control for. The alphas range from 30-38 basis points per month, and are all statistically significantly different from zero at conventional significance levels. None of the loadings on the factors from the Fama and French (2018) six-factor model are economically significant.

Figure 5 further documents the performance of the market-cap-weighted **UGR** trading strategy over the 2013-2019 sample used in our backtest. We can observe that the strategy performs well throughout the sample. The only year with a negative annual return is 2013, when it yielded about -6%. All other years, however, have seen positive returns to the strategy.

Table 3. Backtest results for market-cap-weighted UGR trading strategy

This table shows backtesting results for a trading strategy that goes long stocks with high unexpected government receivables and short stocks with no government receivables. The table reports average returns (r) and alphas on five different factor models (α's) in Panel A, and factor loadings on the factors in the Fama and French (2018) six-factor model (β's) in

Panel B, for portfolios formed based on their unexpected government receivables variable, **UGR**, and defined as follows:

- Portfolio (1) is firms with **GR** = 0 or **GR = N/A**
- Portfolio (2) is firms with **UGR** in bottom tercile
- Portfolio (3) is firms with **UGR** in middle tercile
- Portfolio (4) is firms with **UGR** in top tercile
- Portfolio (4)-(1) is a portfolio that goes long stocks in Portfolio (4) and short stocks in Portfolio (1)

Stocks are market-cap-weighted within portfolios and the portfolio holdings are rebalanced at the end of each month. T-statistics are reported in brackets. The sample includes all U.S. publicly traded ordinary common shares of stock and the period is from January 2013 – December 2019.

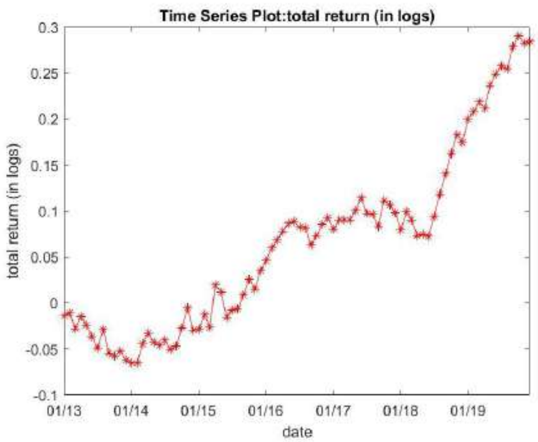
Panel A: Excess returns and alphas from factor models (%/month)

Portfolio	r	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	1.06	-0.10	-0.06	-0.05	-0.05	-0.04
	[2.81]	[-1.90]	[-1.25]	[-1.14]	[-1.14]	[-0.97]
(2)	1.21	0.15	0.07	0.05	0.06	0.03
	[3.33]	[1.11]	[0.53]	[0.34]	[0.44]	[0.21]
(3)	1.04	-0.09	-0.13	-0.16	-0.14	-0.17
	[2.72]	[-0.69]	[-1.01]	`	[-1.05]	[-1.36]
(4)	1.41	0.28	0.26	0.32	0.25	0.32
	[3.65]	[1.99]	[1.86]	[2.39]	[1.78]	[2.32]
(4)-(1)	0.35	0.38	0.32	0.37	0.30	0.36
	[2.19]	[2.27]	[1.96]	[2.36]	[1.87]	[2.26]

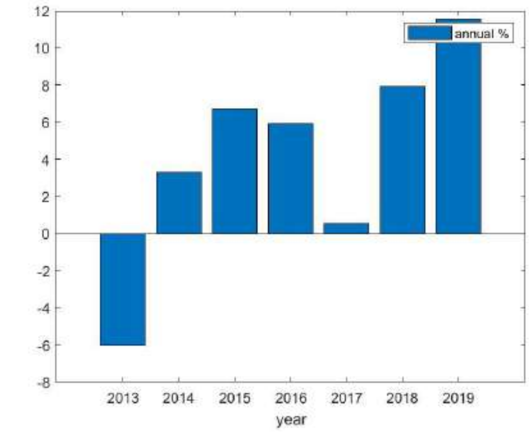
Panel B: Loadings on Fama and French (2018) six-factor model

Portfolio	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{UMD}
(1)	0.99	0.10	-0.02	-0.09	0.02	-0.02
	[68.54]	[4.51]	[-0.64]	[-2.56]	[0.60]	[-0.98]
(2)	0.99	-0.13	-0.06	0.10	0.09	0.08
	[23.02]	[-2.12]	[-0.80]	[0.95]	[0.79]	[1.56]
(3)	1.04	-0.09	0.12	0.13	-0.07	0.09
	[25.27]	[-1.56]	[1.63]	[1.30]	[-0.60]	[1.98]
(4)	0.96	-0.09	-0.02	0.08	-0.06	-0.15
	[22.02]	[-1.37]	[-0.20]	[0.77]	[-0.50]	[-3.10]
(4)-(1)	-0.03	-0.18	0.00	0.17	-0.08	-0.14
	[-0.61]	[-2.45]	[0.01]	[1.38]	[-0.59]	[-2.37]

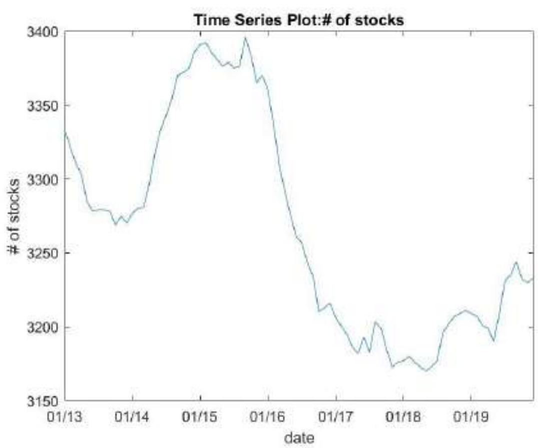
Figure 5. Backtest results for market-cap-weighted UGR trading strategy



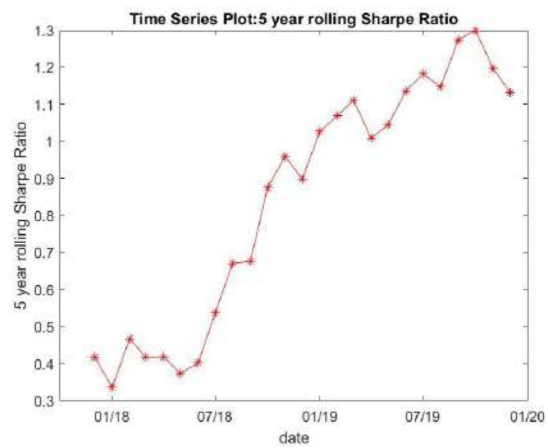
(a) Strategy cumulative return



(b) Strategy performance by year



(c) Combined # of stocks in long and short portfolios



(d) Strategy rolling 5-year Sharpe ratio

Backtesting a market-cap-weighted (UGR) strategy in Russell 1000 universe

While the market-cap-weighting in the **UGR** trading strategy backtested in the previous section alleviates some of the concerns about implementation, the strategy still utilizes the entire cross-section of publicly traded stocks. As a result, its implementation would still have required investors to trade and, in particular, to short tiny stocks.

Thus, in this section we present results for similarly constructed **UGR** trading strategy that only takes positions into stocks in the Russell 1000 universe. The implementation of this trading strategy should be much easier, since Russell 1000 stocks are considered large capitalization stocks, and are thus much easier to trade. Table 4 reports the backtesting results for the **UGR** trading strategy that goes long stocks with high unexpected government receivables and short stocks with no government receivables, only among Russell 1000 stocks.

Table 4. Backtest results for UGR trading strategy within Russell 1000

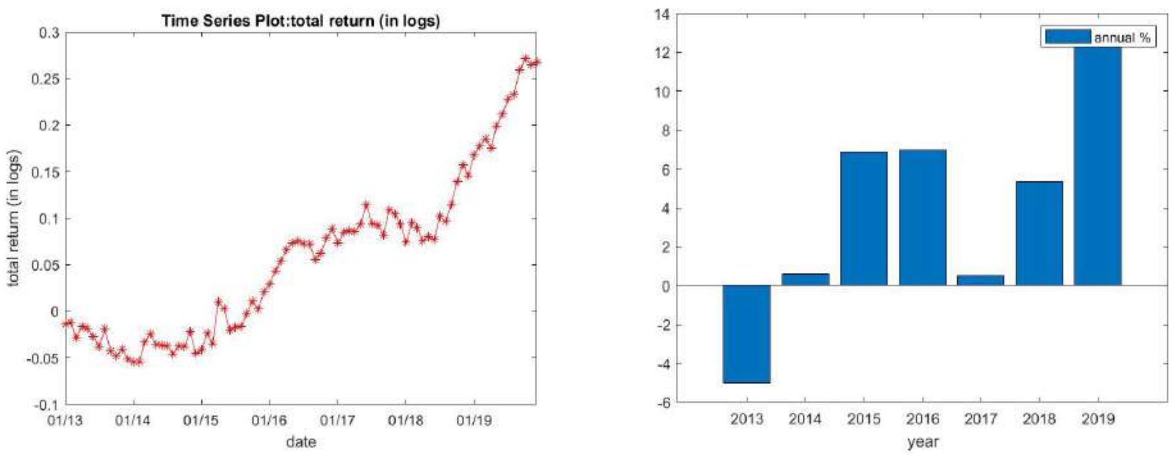
This table shows backtesting results for a trading strategy that goes long stocks with high unexpected government receivables and short stocks with no government receivables. The table reports average returns (r) and alphas on five different factor models (α's) in Panel A, and factor loadings on the factors in the Fama and French (2018) six-factor model (β's) in Panel B, for portfolios formed based on their unexpected government receivables variable, **UGR**, and defined as follows:

- Portfolio (1) is firms with **GR** = 0 or **GR = N/A**
- Portfolio (2) is firms with **UGR** in bottom tercile
- Portfolio (3) is firms with **UGR** in middle tercile
- Portfolio (4) is firms with **UGR** in top tercile
- Portfolio (4)-(1) is a portfolio that goes long stocks in Portfolio (4) and short stocks in Portfolio (1)

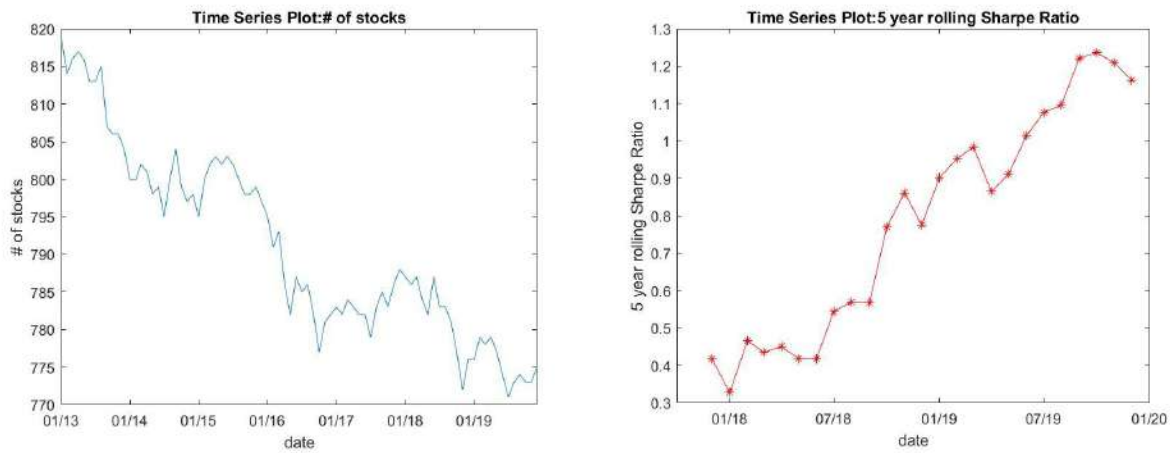
Stocks are market-cap-weighted within portfolios and the portfolio holdings are rebalanced at the end of each month. T-statistics are reported in brackets. The sample includes all stocks in the Russell 1000 index and the period is from January 2013 – December 2019.

Panel A: Excess returns and alphas from factor models (%/month)						
Portfolio	r	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	1.08	-0.05	-0.05	-0.04	-0.04	-0.04
	[2.95]	[-1.10]	[-0.96]	[-0.89]	[-0.87]	[-0.78]
(2)	1.18	0.14	0.05	0.03	0.03	0.01
	[3.24]	[0.90]	[0.32]	[0.19]	[0.22]	[0.04]
(3)	1.09	-0.06	-0.12	-0.17	-0.13	-0.18
	[2.77]	[-0.46]	[-0.90]	[-1.24]	[-0.93]	[-1.31]
(4)	1.41	0.32	0.29	0.34	0.28	0.34
	[3.78]	[2.31]	[2.16]	[2.73]	[2.08]	[2.66]
(4)-(1)	0.33	0.37	0.33	0.39	0.32	0.38
	[2.16]	[2.31]	[2.15]	[2.58]	[2.06]	[2.49]
Panel B: Loadings on Fama and French (2018) six-factor model						
Portfolio	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{UMD}
(1)	0.99	0.00	-0.03	-0.07	0.03	-0.01
	[63.02]	[0.16]	[-1.00]	[-2.01]	[0.80]	[-0.56]
(2)	0.99	-0.15	-0.06	0.13	0.10	0.06
	[20.98]	[-2.21]	[-0.67]	[1.19]	[0.78]	[1.19]
(3)	1.06	-0.09	0.09	0.13	-0.11	0.12
	[24.49]	[-1.47]	[1.16]	[1.31]	[-0.90]	[2.40]
(4)	0.94	-0.15	0.02	0.06	-0.05	-0.15
	[22.76]	[-2.50]	[0.30]	[0.62]	[-0.49]	[-3.22]
(4)-(1)	-0.05	-0.15	0.05	0.14	-0.09	-0.14
	[-1.00]	[-2.15]	[0.57]	[1.17]	[-0.67]	[-2.53]

Figure 6. Backtest results for UGR trading strategy within Russell 1000



(a) Strategy cumulative return **(b)** Strategy performance by year



(c) Combined # of stocks in long and short portfolios **(d)** Strategy rolling 5-year Sharpe ratio

We can observe that the results for this strategy are remarkably close compared to the results for the market-weighted UGR strategy implemented in the entire universe of stocks reported in Table 3. The UGR strategy restricted to the Russell 1000 achieves an average return (annualized Sharpe ratio) of 33 basis points (0.82) compared to the 35 basis points (0.82) for the full universe strategy.

The alphas for the Russell 1000 strategy are even slightly better than the full universe strategy, ranging between 32-39 basis points per month, with even higher t-statistics. This impressive performance can further be seen in Figure 6, where we see that the performance of the Russell 1000 strategy is slightly less negative in 2013 (-4 % vs -6% for the full-universe strategy). Finally, in panel (c) we can observe the much smaller number of stocks needed to trade to exploit this strategy.

Backtesting a synthetic long/short UGR strategy in Russell 1000 universe

Table 5 presents results for a synthetic long/short UGR strategy implemented only within Russell 1000 universe stocks that is even easier implement compared to the strategy examined in the previous section. Portfolio (2) in this table is equivalent to Portfolio (4) in Table 4, that is, the top tercile of UGR stocks within the Russell 1000 index. Portfolio 1, however, differs in that we are looking at the entire market portfolio. This can be thought of a market ETF, which should easier to short and avoid the shorting costs associated with shorting multiple stocks in the short portfolio.

We can observe that the long/short strategy presented here generates similar performance to the one in Table 4. The average return is a statistically significant 27 basis points per month, and the alphas vary between 28 and 34 basis points with t-statistics all above 2. This strategy essentially requires rebalancing each month positions in a portfolio that is long about 100 large cap stocks, and keeping a separate short position in a market ETF. Given the ease of implementation, we believe this strategy could be a powerful source of returns and alpha for asset managers.

Table 5. Backtest results for a synthetic long/short UGR strategy within Russell 1000

This table shows backtesting results for a trading strategy that goes long stocks with high unexpected government receivables and shorts a market ETF. The table reports average returns (r) and alphas on five different factor models (α's) in Panel A, and factor loadings on the factors in the Fama and French (2018) six-factor model (β's) in Panel B, for portfolios formed based on their unexpected government receivables variable, **UGR**, and defined as follows:

- Portfolio (1) is the market portfolio
- Portfolio (2) is firms with **UGR** in top tercile within Russell 1000 stocks
- Portfolio (2)-(1) is a portfolio that goes long stocks in Portfolio (4) and short stocks in Portfolio (1)

Stocks are market-cap-weighted within portfolios and the portfolio holdings are rebalanced at the end of each month. T-statistics are reported in brackets. The sample includes all stocks in the Russell 1000 index and the period is from January 2013 – December 2019.

Panel A: Excess returns and alphas from factor models (%/month)						
Portfolio	r	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	1.14	0.00	0.00	0.00	0.00	0.00
	[3.15]	[2.04]	[6.87]	[0.83]	[3.36]	[2.30]
(2)	1.41	0.32	0.29	0.34	0.28	0.34
	[3.78]	[2.31]	[2.16]	[2.73]	[2.08]	[2.66]
(2)-(1)	0.27	0.32	0.29	0.34	0.28	0.34
	[2.05]	[2.31]	[2.16]	[2.73]	[2.08]	[2.66]
Panel B: Loadings on Fama and French (2018) six-factor model						
Portfolio	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{UMD}
(1)	1.00	0.00	-0.00	0.00	-0.00	0.00
	[2e15]	[1.65]	[-1.30]	[1.46]	[-2.53]	[0.00]
(2)	0.94	-0.15	0.02	0.06	-0.05	-0.15
	[22.76]	[-2.50]	[0.30]	[0.62]	[-0.49]	[-3.22]
(2)-(1)	-0.06	-0.15	0.02	0.06	-0.05	-0.15
	[-1.44]	[-2.50]	[0.30]	[0.62]	[-0.49]	[-3.22]

Backtesting a daily market-cap-weighted UGR strategy within the full universe

Table 6 shows backtesting results for a market-cap-weighted **UGR** trading strategy which is executed in the full universe of stocks and portfolios are rebalanced daily. The daily rebalancing allows us to potentially take advantage of a more frequent updating of the information on forward-looking government receivables. Indeed, if new government contracts are awarded at the beginning of the month, waiting to trade on the **UGR** at the end of the month could result in being too late in that investors have already incorporated the relevant information.

The results reported in Table 6, however, are quite close to the monthly-rebalanced strategy results reported in Table 3. The average daily return is 1.57 basis points, which is not too far off from the 35 basis points per month reported in Table 3. The alphas are slightly higher in magnitude, ranging from 1.59-1.95 basis points per day. The statistical significance of the average returns and alphas is comparable to the one observed in the previous tests as well. We interpret this as evidence that either contracts are typically awarded towards the end of the month or that it takes longer than a few weeks for the information to be incorporated, so the daily rebalancing does not help us in any meaningful way.

Table 6. Backtest results for market-cap-weighted UGR trading strategy

This table shows backtesting results for a daily trading strategy that goes long stocks with high unexpected government receivables and short stocks with no government receivables. The table reports daily average returns (r) and alphas on five different factor models (α's) for portfolios formed based on their unexpected government receivables variable, **UGR**, and defined as follows:

- Portfolio (1) is firms with **GR** = 0 or **GR = N/A**
- Portfolio (2) is firms with **UGR** in bottom tercile
- Portfolio (3) is firms with **UGR** in middle tercile
- Portfolio (4) is firms with **UGR** in top tercile
- Portfolio (4)-(1) is a portfolio that goes long stocks in Portfolio (4) and short stocks in Portfolio (1)

Stocks are market-cap-weighted within portfolios and the portfolio holdings are rebalanced at the end of each day. T-statistics are reported in brackets. The sample includes all U.S. publicly traded ordinary common shares of stock and the period is from January 2013 – December 2019.

Daily excess returns and alphas from factor models (bps/day)						
Portfolio	r	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	5.39	-0.24	-0.11	-0.10	-0.08	-0.07
	[2.84]	[-1.09]	[-0.56]	[-0.51]	[-0.44]	[-0.36]
(2)	5.76	0.73	0.44	0.37	0.36	0.27
	[2.95]	[1.25]	[0.81]	[0.71]	[0.66]	[0.51]
(3)	5.42	0.14	-0.01	-0.02	-0.06	-0.08
	[2.68]	[0.27]	[-0.02]	[-0.04]	[-0.12]	[-0.16]
(4)	6.74	1.67	1.60	1.68	1.54	1.63
	[3.41]	[2.68]	[2.61]	[2.82]	[2.52]	[2.75]
(4)-(1)	1.57	1.95	1.72	1.79	1.59	1.67
	[2.05]	[2.57]	[2.37]	[2.51]	[2.22]	[2.36]

CONCLUSION AND FURTHER RESEARCH

The evidence presented in this article strongly suggests that equity investors do not promptly incorporate information about government contracts into stock prices and that it can be a significant strong predictor of cross-sectional equity returns.

In particular, the fact that it is possible to clearly calculate the receivables under any US federal contract remains widely unknown. We find that the signaling power of new government contracts in the context of already existing business with the government could be significant. The unexpected government receivables (UGR) signal we develop shows remarkable performance in our backtests, even when it is used in a trading strategy that would have been trivial to implement. The forward-looking receivables data by TenderAlpha offers a few steps of aggregation that are not available through any raw information on contract announcements. It is specifically designed to leverage the UGR effect as compared to value of expected receivables (and thus size of existing business with the federal government) at any point in time and over any given period of time.

Our conclusion is that figuring out information related to government receivables and the timing of when investors price that information could lead to even stronger predictors of stock returns for both traditional suppliers to the federal government and for unexpected winners of large contracts.

Nevertheless, further research is needed, since the backtests presented in this document only barely touch the surface of what may be available in terms of signals predicting cross-sectional equity returns derived from government receivables.

The signals presented thus do not take into account any of the fundamentals of the firms. Perhaps scaling the government receivables by an accounting variable, such as total revenues, or total assets, could bring additional information relevant for future returns. It is easy to see how a firm that is more reliant on government receivables could be more affected by a large change in its government receivables relative to their total revenues. If investors are slow to incorporate this information, then a signal exploiting this effect could yield even stronger performance.

Similarly, benchmarking the receivables relative to the industry could also result in a more meaningful signal. Different industries have varying degrees of exposure and dependence on government contracts, so looking at the government receivables relative to the median or an upper percentile in the industry could also be informative.

Ultimately, the evidence presented here strongly suggests that equity investors do not promptly incorporate all information about government contracts into stock prices. This is consistent with an extensive academic literature in behavioral finance on slow diffusion of information into stock prices (e.g., Lo and MacKinlay, 1990; Cohen and Frazzini, 2008; Frazzini and Lamont, 2008; Cohen and Lou 2012; Cohen, Diether, and Malloy 2013; etc.).

APPENDIX

Figure 7: Merged observations - relative to all publicly traded stocks in US

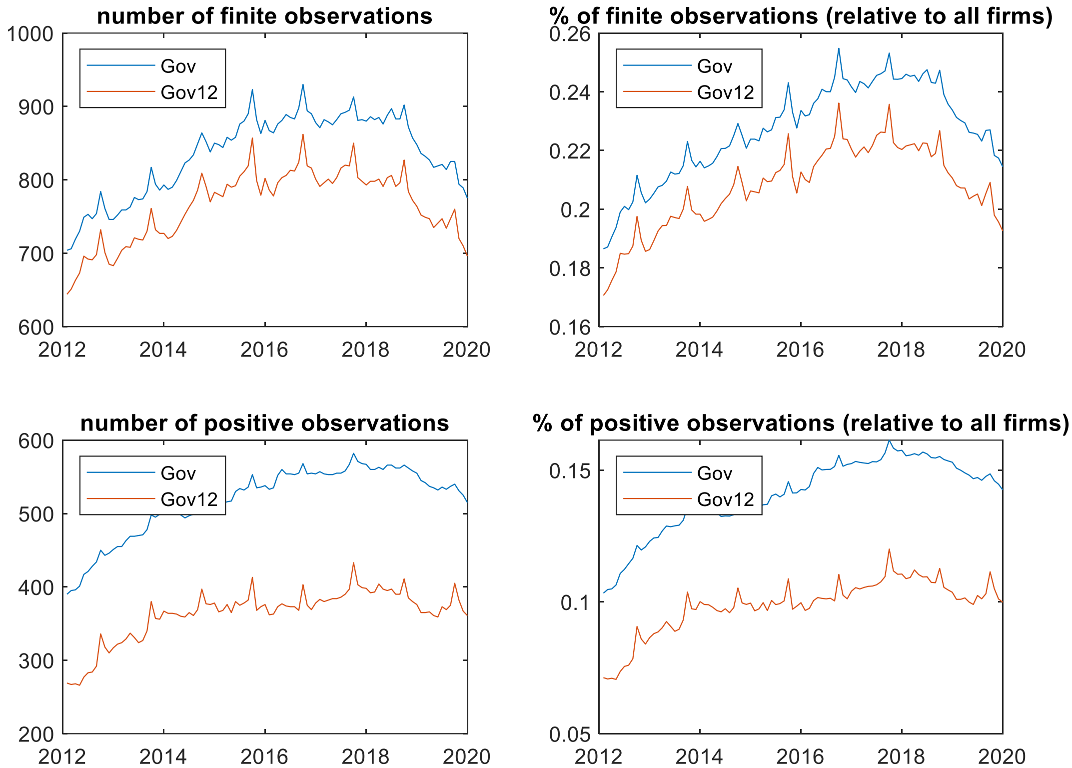


Figure 8: Number of firms in short and long portfolio

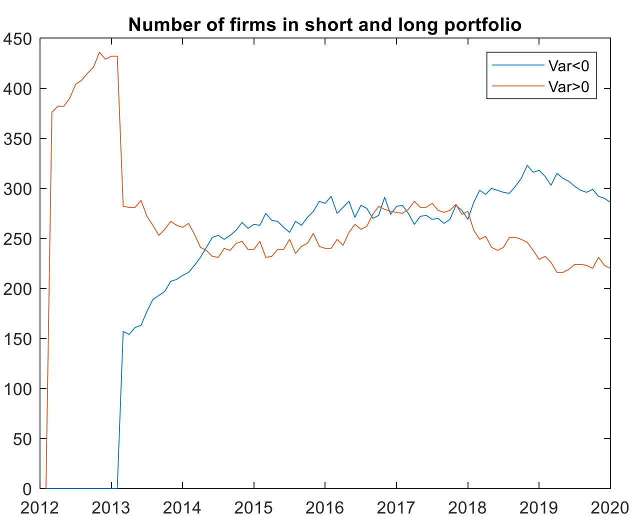


Figure 9: Data merge: stock-day observations on forward-looking receivables from government contracts

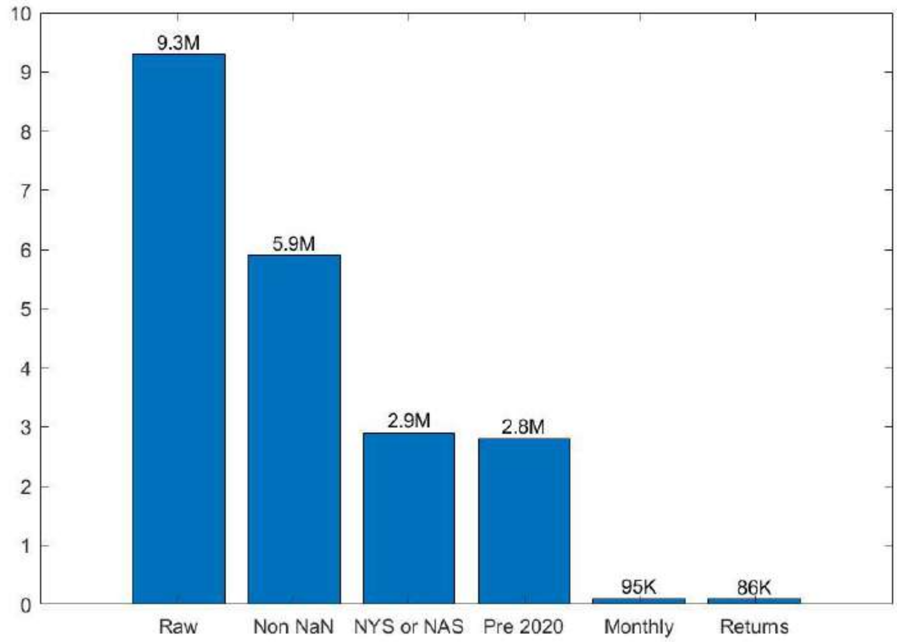
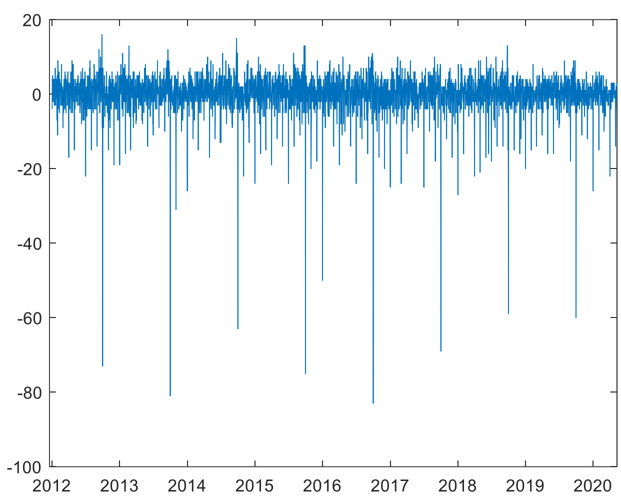


Figure 10: Daily change in the number of firms

We report a drop in # of observations each year on October 1, which is driven by the fact that the fiscal year end for the U.S. government is September 30.



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