Three essays in financial economics

Author:
Rouxelin, Florent

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Three Essays in Financial Economics

Florent Rouxelin

A thesis in partial fulfilment of the requirements for the degree of

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This PhD dissertation is made up of three stand-alone research projects. One on financial accounting and macroeconomics while the two others are empirical asset pricing projects, in the equity and currency markets.

In the first project, I examine whether aggregate cost stickiness predicts future macro-level unemployment rate. I find that a one-standard-deviation-higher cost stickiness in recent quarters is followed by a 0.23 to 0.26-percentage-point-lower unemployment rate in the current and following quarter. In out-of-sample tests, I find significant reductions in the root-mean-squared-errors upon incorporation of cost stickiness for all models. These findings suggest that professional macro forecasters do not fully incorporate the information contained in cost stickiness.

In the second project, I investigate the impact of crude oil balance of trade on the cross-section of currency returns for 36 countries. I find that a portfolio of currency sorted on oil balance of trade is priced and induces an annual risk premium ranging from 2.4 to 2.9%. I conduct the analysis using individual currencies and portfolios as test assets, both leading to the same conclusion. I also find that characteristics subsume factor beta and, hence, confirm results in the equity market (Chordia, Goyal and Shanken 2015). More interestingly, I show that the net oil balance of trade characteristic, specific to each country and varying over time, contains incremental information relative to the carry characteristic that explains currency excess returns.

In the third project, I explore the effect of time-varying arbitrage capital availability in the cross-section of abnormal equity returns. I investigate the relationship between arbitrage capital, proxied by a market wide-liquidity measure introduced by Hu, Pan and Wang (2013), and the future performance of a set of eleven well-known pricing anomalies. When arbitrage capital is abundant, investors are able to deploy arbitrage strategies more successfully, which leads to lower future profitability of pricing anomalies. In contrast, when arbitrage capital is scarce, investors are unable to deploy enough capital to take advantage of pricing anomalies, yielding higher profitability of the anomaly strategies subsequently. Consequently, as a priced factor, time-varying arbitrage capital helps to explain the cross-sectional returns of pricing anomalies.

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Abstract

This PhD dissertation is made up of three stand-alone research projects. One on financial accounting and macroeconomics while the two others are empirical asset pricing projects, in the equity and currency markets.

In the first project, I examine whether aggregate cost stickiness predicts future macro-level unemployment rate. I find that a one-standard-deviation-higher cost stickiness in recent quarters is followed by a 0.23 to 0.26-percentage-point-lower unemployment rate in the current and following quarter. In out-of-sample tests, I find significant reductions in the root-mean-squared-errors upon incorporation of cost stickiness for all models. These findings suggest that professional macro forecasters do not fully incorporate the information contained in cost stickiness.

In the second project, I investigate the impact of crude oil balance of trade on the cross-section of currency returns for 36 countries. Using classical asset pricing methodology, I find that a long/short quintile portfolio of currency sorted on oil balance of trade is priced and induces an annual risk premium ranging from 2.4 to 2.9%. I conduct the analysis using individual currencies and portfolios as test assets, both leading to the same conclusion. I also find that characteristics subsume factor beta and, hence, confirm results in the equity market (Chordia, Goyal and Shanken 2015). More interestingly, I show that the net oil balance of trade characteristic, specific to each country and varying over time, contains incremental information relative to the carry characteristic that explains currency excess returns. The fact that not only oil price but also oil net balance of trade plays a role in asset pricing is completely new to the literature.

In the third project, I explore the effect of time-varying arbitrage capital availability on the cross-section of abnormal equity returns. I investigate the relationship between arbitrage capital, proxied by a market wide-liquidity measure introduced by Hu, Pan and Wang (2013), and the future performance of a set of eleven well-known pricing anomalies. When arbitrage capital is abundant, investors are able to deploy arbitrage strategies more successfully, which leads to lower future profitability of pricing anomalies. In contrast, when arbitrage capital is scarce, investors are unable to deploy enough capital to take advantage of pricing anomalies, yielding higher profitability of the anomaly strategies subsequently. Consequently, as a priced factor, time-varying arbitrage capital helps to explain the cross-sectional returns of pricing anomalies.

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The PhD program is a long journey. I remember my excitement when I opened the official acceptance letter, but not as if it were yesterday. More people than I can cite here helped me along the way. For that, I owe thanks to many. Their generosity and expertise made this complex journey possible.

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Contents

Chapter 1. Introduction

My PhD thesis consists of three independent essays: one on aggregate cost stickiness used as a predictor of unemployment rate, and two on the prediction of the cross-section of asset returns, in the currency and equity market, respectively. As independent essays, they all share the same underlying motivation and desire to forecast macroeconomic or financial variables.

Throughout this dissertation, I have been captivated by means of improving existing predictions. This interest is of prime importance as predicting macroeconomic variables is one of the major tasks faced by monetary decision-makers such as policy makers and investors. Yet, in the public space, accurate forecasting of unemployment is difficult, and the press regularly criticizes the accuracy of forecasts used for policy-making decisions by the Federal Reserve[1]. Turning to the financial markets, successfully predicting asset returns is the *"holy grail"* for any asset management firm. My three essays investigate different types of predictive models-both in the time-series and cross-sectional framework. Each essay also proposes a new variable or characteristic susceptible to contain valuable information to forecast the quantity of interest.

In the first essay, I examine whether aggregate cost stickiness predicts future macro level unemployment rate. I incorporate aggregate cost stickiness into three different classes of forecasting models studied in prior literature, and demonstrate an improvement in forecasting performance for all three models. In particular, I incorporate the cost-stickiness

[1] See, for example, "Watch US unemployment to gauge interest rate direction. Accuracy of the Federal Reserve's forecast is in doubt," *Financial Times*, February 19, 2014. In the academic literature, Stock and Watson (2003) argue that, due to structural changes in the overall U.S. economy, any single economic indicator is unlikely to be a reliable and stable predictor for macroeconomic states. Furthermore, Fildes and Stekler (2002) claim that macroforecasters might have cognitive bias or be motivated by factors other than accuracy, so that their forecasts may contain biases and lack efficiency. Fildes and Stekler (2002) and Stekler (2007) call for research exploring additional information sets into macroeconomic forecasting models.

measure in a VAR analysis that forecasts the rates of inflows and outflows to unemployment (i.e., the probabilities that an employed worker becomes unemployed and that an unemployed worker obtains employment), and then plug these flow estimates into a law of motion for unemployment to produce unemployment rate forecasts. Incorporating the cost-stickiness measure reduces the root-mean square errors by up to 10-14.6% and up to three quarters ahead relative to the original version of the model introduced by Barnichon and Nekarda (2012). As further evidence, an impulse-response graph indicates that a one-standard-deviation exogenous shock to cost stickiness leads to a reduction in unemployment of approximately 5 basis points that persists for 4 quarters. My dedication to improve of the cutting edge unemployment model using cost-stickiness has been recognized and rewarded by an acceptance of this first essay in *The Accounting Review* (forthcoming, July 2018).

While the first essay mainly employs time-series models to predict unemployment rate, the second and the third essays consider predictability in the cross-section of asset returns in different asset markets. The time series strategy takes a directional position on an asset by only looking back at its own performance during the ranking period, and not by basing on its relative rank across a cross-section of different assets.

The second essay investigates the cross-sectional predictability of currency returns using countries' oil balance of trade, comparing its effect among countries at each time period. Using the Generalized Method of Moments (Hansen 1982) and the Fama and MacBeth (1973) two-step procedure, I find that a global oil imbalance factor generates a risk premium ranging from 2.4-2.9% per annum, and that the oil balance of trade characteristic of is able to predict future currency excess returns.

The third essay examines the predicting power of time-varying arbitrage capital on the future performance of a set of well-known pricing anomalies in the equity market. Using a combination of cross-sectional and time series techniques, I prove that abundance of arbitrage capital in the current time period leads to periods of lower future profitability of the pricing anomalies. In contrast, the lack of arbitrage capital in the current time period leads to higher future profitability of the pricing anomalies. As a priced factor, time-varying arbitrage capital is a strong predictor of anomaly returns.

Chapter 2. Aggregate Cost Stickiness in GAAP Financial Statements and Future Unemployment Rate

Abstract

We examine whether aggregate cost stickiness predicts future macro level unemployment rate. We incorporate aggregate cost stickiness into three different classes of forecasting models studied in prior literature, and demonstrate an improvement in forecasting performance for all three models. For example, when adding cost stickiness to an OLS regression, which includes a battery of macroeconomic indicators and control variables, we find that a one-standard-deviation-higher cost stickiness in recent quarters is followed by a 0.23 to 0.26-percentage-point-lower unemployment rate in the current and following quarter. In out-of-sample tests, we find significant reductions in the root-mean-squared-errors upon incorporation of cost stickiness for all three models. Additional tests suggest that professional macro forecasters, particularly those employed in nonfinancial industries, do not fully incorporate the information contained in cost stickiness. Finally, we find a stronger predictive power of cost stickiness towards the end of recessionary periods; we also assess cross-sectional variation of this predictive ability.

1. Introduction

Predicting unemployment is one of the major tasks faced by policy makers. Rising unemployment often triggers intervention by the Federal Reserve and the government as part of their monetary and fiscal policies. Yet, accurate forecasting of unemployment is difficult, and the press regularly criticizes the accuracy of forecasts used for policy-making decisions by the Federal Reserve.[2] In this paper, we study the predictive power of a new aspect of cost behavior studied in the recent accounting literature—cost stickiness.

A growing body of literature in accounting, beginning with Anderson, Banker, and Janakiraman (2003), studies cost stickiness. Costs are considered sticky if "they increase more when activity rises than they decrease when activity falls by an equivalent amount." Cost stickiness captures the asymmetry in managers' decision to commit resources when they face uncertain future activity levels and resource adjustment costs (Banker and Byzalov 2014).

In this paper, we examine whether incorporating cost stickiness in unemployment forecasting models improves forecasting performance. We build on the concept of sticky costs by constructing a time-varying measure of aggregate cost stickiness for all public firms in the United States. Since periods of higher aggregate cost stickiness correspond to resource retention by firms facing sales declines, we expect such periods to be followed by periods of relatively low unemployment. When estimating the degree of stickiness, we focus on

[2] See, for example, "Watch US unemployment to gauge interest rate direction. Accuracy of the Federal Reserve's forecast is in doubt," *Financial Times*, February 19, 2014. In the academic literature, Stock and Watson (2003) argue that, due to structural changes in the overall U.S. economy, any single economic indicator is unlikely to be a reliable and stable predictor for macroeconomic states. Furthermore, Fildes and Stekler (2002) claim that macroforecasters might have cognitive bias or be motivated by factors other than accuracy, so that their forecasts may contain biases and lack efficiency. Fildes and Stekler (2002) and Stekler (2007) call for research exploring additional information sets into macroeconomic forecasting models.

operating costs (sum of cost of goods sold (COGS) and selling, general and administrative expenses (SG&A)) because labor costs are a major component of these cost categories for most firms.

We consider three different forecasting models of unemployment rate. Each model represents a different approach to the prediction task. In addition to evaluating the in-sample predictive ability of cost stickiness for each model, we also assess the improvement in out-of-sample forecasting performance when cost stickiness is included as an additional predictor variable. In line with the forecasting literature (e.g., Stark 2013; Meyer and Tasci 2015), we evaluate forecasting performance using root mean-squared-errors (RMSEs).

We begin by examining an ordinary least squared (OLS) regression model that predicts changes in unemployment based on several macroeconomic and accounting indicators. Our starting point is Okun's law (Okun 1963), which captures the relationship between output (*GDP*) growth and unemployment rate changes. We also include in the OLS regression a battery of controls for other macroeconomic indicators, aggregated accounting variables, factors previously shown to predict unemployment, and macro variables that are correlated with cost stickiness. We find that cost stickiness is inversely associated with the change in unemployment rate over the current quarter (i.e., the "nowcast") and the following four quarters. The effect is economically and statistically significant: a one-standard-deviation-greater measure of aggregate cost stickiness is associated with a reduction of 26 (23) basis points in unemployment rate in the current (following) quarter. The mean unemployment rate during our sample period was 6.1%.

Second, we consider vector autoregression (VAR) models. The VAR approach takes into account time-series interdependencies of the different macroeconomic variables of interest.

One major disadvantage of VAR models, however, is the need to estimate a very large number of coefficients (Robertson and Tallman 1999). In particular, compared to OLS approaches, the number of cross-sectional predictors that a VAR model can handle is relatively limited because the number of coefficients to be estimated grows exponentially with the number of variables. We consider two VAR models that have been used in the literature. We first build on the VAR model of Stock and Watson (2001) (hereinafter "SW"), who model the evolution of the unemployment rate following Taylor's (1993) rule. The SW model relates unemployment rate, inflation, and federal funds rates. When adding cost stickiness as an additional vector component to the SW VAR model, the resulting impulse-response function shows that a one-standard-deviation exogenous shock to aggregate cost stickiness leads to a 22-basis-point reduction in unemployment rate that persists up to 10 quarters.

Third, we estimate another VAR specification developed more recently by Barnichon and Nekarda (2012) (hereinafter "BN"). The BN model involves forecasting the flows in and out of the workforce separately, and then relating these flows to unemployment rate forecasts. This model represents a novel approach to forecasting unemployment rate and claims substantial improvement in near-term forecasts over existing approaches, including nonlinear models studied in prior literature (Meyer and Tasci 2015).[3] This approach uses initial unemployment insurance claims and job vacancy postings as leading indicators of workforce flows. We continue to find incremental predictive contribution for cost stickiness, albeit more muted: a one-standard-deviation orthogonalized shock to cost stickiness leads to a reduction

[3] For example, Barnichon and Nekarda (2012) calculate that their model produces unemployment rate forecasts with RMSE which is 30% lower than for forecasts produced by professional macroforecasters over the period 1976 to 2006. In its blog section, the New York Times describes the model as "innovative and impressively accurate" (Economix blog, "Forecasting Unemployment", by Annie Lowrey, October 5, 2012).

in unemployment rate of approximately 5 basis points which persists for four quarters.

In out-of-sample analyses, we find that the forecasting performance of all three models improves when incorporating cost stickiness. For example, incorporating cost stickiness into the BN model reduces the RMSEs for horizons of up to three quarters. The reduction is both economically and statistically significant: for one-quarter ahead prediction, for example, the reduction in RMSE amounts to 11%. This reduction is even larger (18%) when we estimate cost stickiness using a subsample of labor-intensive firms only. These firms are large employers in the U.S., and we would therefore expect, and find, cost stickiness exhibited by these firms to be more strongly linked to labor retention behaviors.

Comparing different models for forecasting unemployment rate, Meyer and Tasci (2015) conclude that, while the BN model produces the lowest RMSEs in the near term (up to one quarter ahead), for longer horizons, forecasts issued by professional macroforecasters tend to be the single best predictor of unemployment rate. Hence, in our next set of tests, we examine the extent to which these professional forecasts incorporate the information contained in cost stickiness. In particular, we examine forecasts made by respondents to the Federal Reserve Bank of Philadelphia's quarterly survey of professional forecasters (SPF).

To do so, we combine forecasts produced by each of the three statistical models examined, a technique commonly used in prior macroeconomics literature (e.g., Bates and Granger 1969; Wright 2008). Since each forecasting model makes use of a different information set, the combined forecasts should reflect information from all the different sources and therefore be more accurate, i.e., have lower RMSEs. We follow, e.g., Barnichon and Nekarda (2012), and we combine the forecasts by assigning weights which are determined in a dynamic fashion. Each quarter, we run OLS regressions of historical realizations on past forecasts from the different models to determine the optimal weight for each model's forecasts. These weights are then applied to the current quarter's forecasts to produce the combined forecasts. We find that the combined forecasts from statistical models with cost stickiness outperform professional macroforecasters up to two quarters ahead. For comparison, the combined forecasts from the statistical models without cost stickiness outperform professional macroforecasters for the current and next quarters only. Thus, it appears that SPF panelists at least partially overlook cost stickiness. Additionally, we consider the industry in which the professional forecaster is employed. While macroforecasters employed in both financial and nonfinancial industries tend to overlook some of the information contained in cost stickiness, macroforecasters employed in nonfinancial industries do so to a greater extent.

Next, we consider recessionary periods, in which the unemployment rate is particularly difficult to predict (Montgomery, Zarnowitz, Tsay, and Tiao 1998). We expect that the predictive power of cost stickiness will be more salient towards the end of economic recessions than at the start. At the beginning of a recession, a higher proportion of firms experience a reduction in sales and these firms tend to exhibit "anti-sticky" cost behavior—that is, the reduction in costs as sales fall is much steeper than the increase in costs when sales recover (Weiss 2010; Banker, Fang, and Mehta 2012). The higher proportion of firms with sales reduction and exhibiting anti-stickiness reduces the predictive ability of the aggregate cost stickiness that we observe for the entire sample. Yet, towards the end of a recession, managers of all firms (including those that experienced sales decreases) begin to retain slack resources in anticipation of sales recovery, leading to an increase in informativeness of cost stickiness. We find results confirming our expectation that cost stickiness is more useful in forecasting unemployment when recessions end.

Finally, we estimate cost stickiness for subsamples of firms in situations where the predictive power of the measure is likely to be stronger.[4] We find that cost stickiness for the following groups of firms improves predictive performance: (a) firms with stronger governance mechanisms in place. In these firms, cost stickiness is less likely to be upwardly biased due to managerial incentives (Chen, Lu, and Sougiannis 2012; Kama and Weiss 2013); (b) less asset-intensive firms. In highly asset-intensive firms, cost stickiness is more likely to capture asset-related adjustment costs and less likely to reflect labor-related adjustment costs; (c) firms in concentrated industries. In concentrated industries, the sensitivity of cost stickiness to changes in unemployment is more pronounced (Qualls 1979; Domowitz, Hubbard, and Petersen 1986; Bils 1987).

The results in this paper are robust across multiple methods for estimating cost stickiness: the traditional model (Anderson, Banker, and Janakiraman 2003) described above, Weiss's (2010) firm-level measure aggregated across all firms, and a linear specification (Balakrishnan, Labro, and Soderstrom 2014).

Our study contributes to several streams of literature. First, we contribute to the cost accounting literature on sticky costs (Anderson, Banker, and Janakiraman 2003; Balakrishnan, Peterson, and Soderstrom 2004; Banker and Chen 2006; Anderson, Huang, and Janakiraman 2007; Weiss 2010; Kama and Weiss 2013) and the economic literature on wage rigidity address the question on how firms adjust the quantity and cost of their labour input to falls in demand. One of the central questions researchers have attempted to address is whether wages are downwardly rigid and why (Sharpino and Stiglitz, 1984; Akerlof and

[4] We report the results using OLS models, because the interpretation is straightforward. We reach similar conclusions when using the other models.

Yellen 1990). This body of literature includes field studies and economic experiments. There is a remarkable consensus among the conclusions of all these investigations showing that when firms face a fall in demand, they experience difficulties cutting wages. Instead, firms choose hiring fewer workers, reducing working hours, decreasing their use of agency workers and allocating more work to junior staff (Baker, Gibbs and Holmstrom 1994, Wilson 1996 and Altonji and Devereux 2000). When constructed solely based on SG&A, our cost stickiness measure is mostly composed of labour costs and relates closely to the concept of wage rigidity. Costs are considered sticky if they increase more when activity rises than they decrease when activity falls by an equivalent amount. Cost stickiness captures the asymmetry in managers' decision to commit resources when they face uncertain future activity levels and resource adjustment costs (Banker and Byzalov 2014). Building on the rigidity wage literature, we acknowledge impediments to cut wages and we construct a time-varying measure of aggregate cost stickiness for all public firms in the United States. Using microeconomic (firm level) data, this measure focuses on the aggregate amount of wages and salaries to create a macro level variable. Since periods of higher aggregate cost stickiness correspond to resource retention by firms facing sales declines, we expect such periods to be followed by periods of relatively low unemployment and vice versa. To the best of our knowledge, we are the first to link aggregate cost stickiness to a macroeconomics topic by showing that cost stickiness helps predict future unemployment rate.

Second, we contribute to the macroeconomics literature on unemployment rate forecasting. We incorporate cost stickiness in three empirical models that represent different approaches to forecasting unemployment. We show that cost stickiness improves the forecasting ability of all three models. Furthermore, we show that cost stickiness is at least partially overlooked by some professional macroforecasters. Relatedly, our investigation contributes to the literature on the cyclicality of costs and output prices.[5] Our findings indicate that cost stickiness is countercyclical to unemployment (i.e., procyclical to the business cycle)—when it increases unemployment falls, and when it decreases unemployment increases.[6]

Third, our paper integrates a cost accounting research topic, asymmetric cost behavior, with the financial accounting literature on the usefulness of aggregate accounting information in predicting the macroeconomy (e.g., Jorgensen, Li, and Sadka. 2012; Bonsall, Bozanic, and Fischer 2013; Konchitchki and Patatoukas 2014; Gallo, Hann, and Li 2016; Nallareddy and Ogneva 2017; Kalay, Nallareddy and Sadka, 2017). The importance of integrating insights from financial and managerial accounting research and other literatures has long been acknowledged (e.g., Hemmer and Labro 2008; Banker and Byzalov 2014).

The remainder of the paper proceeds as follows. We review related literature and develop our main prediction in Section 2. Section 3 describes the data and provides descriptive statistics. Sections 4 and 5 present the results of the analysis. Section 6 concludes.

1. Institutional Details, Related Literature, and Main Prediction

In this section, we provide institutional details about unemployment rate forecasting in the U.S. We also briefly review the literatures on the information content of cost stickiness and the cyclicality of costs and margins. Lastly, we present our main hypothesis.

[5] See Rotemberg and Woodford, 1999 for review. While this literature a has examined the relationship between the marginal cost, output prices, and the business cycle, its main objective was not to predict unemployment *per se*.

[6] Because cost stickiness is inversely related to the change in cost of the firm in the short run, this paper's findings support the notion of countercyclical marginal cost.

1.1. Unemployment Rate Forecasting in the U.S.

In the U.S., an important source of macroeconomic forecast data is provided by the Survey of Professional Forecasters, conducted quarterly. The panelists are anonymous and they are chosen from a broad range of industries—both financial (e.g., insurance, investment banking, commercial banking, payment services, hedge funds, mutual funds, association of financial service providers, and asset management) and nonfinancial (manufacturers, universities, forecasting firms, investment advisors, research firms and consulting firms). The survey is usually sent to panelists at the end of the first month of each calendar quarter (timed to concur with the release of advance GDP forecasts by the Bureau of Economic Analysis). Panelists are asked to provide forecasts for 32 economic variables for the current quarter through four quarters ahead.[7] The summary forecasts are released to the public by the middle of the following month.

According to a special survey of SPF panelists conducted in November 2009 (Stark 2013), when generating their forecasts, most panelists use a combination of mathematical models and subjective adjustments reflecting the individual forecaster's expert judgment. Mathematical models include those seeking statistical patterns in particular time-series characteristics of the variables of interest and those of a structural nature that make use of links among several macroeconomic variables capturing different sectors of the economy. One such relationship is the empirically-documented association between output growth and unemployment changes (Okun 1963; commonly referred to as Okun's Law).[8]

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[7] More recently, the survey has started asking about forecasts for the current year and for the next year.
[8] See "Do Forecasters Believe in Okun's Law? An Assessment of Unemployment and Output Forecasts" (Ball, Jalles, and Loungani, IMF Working Paper, February 2014).

1.2. The Information Content of Cost Stickiness

Anderson, Banker, and Janakiraman (2003) document empirically that SG&A costs behave in a sticky manner: costs increase by 0.55% when sales increase by 1% but decrease by only 0.35% when sales decline by 1%. The researchers ascribe this effect to deliberate managerial decisions about committed resources when there is uncertainty about future demand for their firms' products. Follow-up papers have offered more detailed explanations.

The first explanation relates to resource adjustment costs (Banker, Byzalov, and Chen 2013). Greater magnitude of adjustment costs leads to greater cost stickiness because the firm's behavior under optimal decision-making is asymmetric. With labor, severance and training costs can be significant. Faced with declining sales, managers are reluctant to fire workers because retaining the unused resources helps avoid the large staff termination costs and future training costs when rehiring. Conversely, when activity increases, although managers may be reluctant to hire more workers because of the adjustment costs, the increase in current sales can only be achieved if additional workers are hired, thus the reluctance effect is likely to be more muted (Banker and Byzalov 2014; Banker, Byzalov, and Chen 2013; Balakrishnan and Gruca 2008).

A second explanation suggests that cost stickiness is indicative of managerial expectations regarding future demand for the firm's products (Banker, Byzalov, Ciftci, and Mashruwala 2014). Managerial optimism weakens cost response to current sales decreases and amplifies cost response to current sales increases, thereby resulting in increased cost stickiness.

A third explanation relates to managerial incentives and agency costs (Anderson, Banker, and Janakiraman 2003; Chen, Lu, and Sougiannis 2012; Kama and Weiss 2013). Empire-building managers, motivated to maximize resources under their control, will cut resources only moderately when sales decrease and will expand resources excessively when sales increase.[9]

1.3. Cost Behavior and the Business Cycle

A related stream of literature concerns the cyclicality of marginal costs and markups (a markup being defined in this literature as the ratio of the price to the marginal cost—that is, the reciprocal of the real marginal cost).[10] This literature to date has produced conflicting results (Carlton and Perloff, 2005).[11] While many studies document a countercyclical or acyclical real marginal cost or a procyclical markup (Domowitz, Hubbard, and Petersen 1986; Hall 1986, 1988), more recent research documents procyclical real marginal costs (i.e., acyclical markup). Bils (1987) and Phelps (1994) estimate marginal cost for the case of a Cobb-Douglas production function, in which marginal cost is equal to the labor share. Empirically, they find relatively small negative correlations between labor share and output. Follow-up research (Rotemberg and Woodford 1996, 1999) improved the estimation by incorporating additional assumptions. The resulting marginal cost estimate is more procyclical.

1.4. Main Prediction

We expect the degree of cost stickiness in employing firms to reflect two main types of

[9] In the case of costs related to employment, Williamson (1963) argues that managerial incentive to expand staff "may be difficult to resist," since the "promotional opportunities in a fixed size firm are limited." Consequently, when agency issues are severe, cost stickiness is biased upward.

[10] With the development of New Keynesian (NK) models, this literature has explored the cyclical behavior of costs and output prices. Under the NK model, sticky prices, combined with procyclical marginal cost, result in increased real marginal cost (or reduced markups) at times of expansion and decreased marginal cost in times of contraction.

[11] The authors state that "several recent studies… reach different conclusions, so this area remains one of active research" (p. 578).

information that can aid in predicting future unemployment. First, the degree of cost stickiness reflects the magnitude of the adjustment costs—including firing and hiring costs—prevalent in the legal and operating environment of the employing firm. Second, the degree of cost stickiness reflects managerial expectations about the future state of the product and labor markets.

When aggregate cost stickiness is higher, firms retain employees even when facing declining sales. Therefore, we would expect unemployment not to rise or even drop in the subsequent quarters. If, on the other hand, firms display willingness to terminate employees when experiencing sales declines, we would expect unemployment to rise in the short term.

We state our main hypothesis formally as follows:

Ceteris paribus, aggregate cost stickiness predicts future change in unemployment rate. Specifically, high levels of cost stickiness are associated with subsequent reductions in macrolevel unemployment rate.

2. Data

Our sample period is Q1:1985 to Q4:2013. We begin our sample in 1985, following the cost stickiness literature (Anderson, Banker, and Janakiraman 2003). We obtain quarterly data on civilian rates of unemployment from the Philadelphia Fed's Real-Time Data Set (for historical actual and forecast values).[12] The Survey of Professional Forecasters has been administered by the Philadelphia Fed since Q2:1990 and previously by the American

[12] The historical civilian rates of unemployment are compiled by the Philadelphia Fed using *Employment and Earnings* publications issued by the Bureau of Labor Statistics.

Statistical Association and the National Bureau of Economic Research.[13] We require future realizations up to four quarters ahead in order to conduct out-of-sample tests; hence, we end our sample period in 2013.

We collect quarterly financial statements data from the Compustat North America quarterly database. Compared to estimation using annual data, which has commonly been used in prior research on cost stickiness (e.g., Anderson, Banker, and Janakiraman 2003), quarterly financial statements are more timely and therefore reflect more recent relevant managerial actions. In addition, the Philadelphia Fed compiles forecasts on a quarterly basis, and, therefore, using quarterly data sources provides a natural alignment with the forecast generation process.

We implement the methodology in Anderson, Banker, and Janakiraman (2003) to estimate cost stickiness, adapting it to use quarterly Compustat data on sales revenue (dataitem *saleq*), SG&A expenses (*xsgaq*), and cost of goods sold (*cogsq*). Given our research question, our primary construct of interest is labor cost stickiness. We combine expenses for COGS and SG&A to proxy for labor cost.[14] We use available data for all U.S. companies available on Compustat. In line with prior research (e.g., Banker and Byzalov 2014), we winsorize all continuous variables at the 0.5% tails in each quarter.

We estimate the following regression each quarter:

$$\log\left[\frac{(COGS+SG\&A)_{i,q}}{(COGS+SG\&A)_{i,q-4}}\right] = \beta_0 + \beta_1 \log\left[\frac{SALES_{i,q}}{SALES_{i,q-4}}\right] + \beta_2 I\_Decrease_{i,q} \times \log\left[\frac{SALES_{i,q}}{SALES_{i,q-4}}\right] + e_{i,q} \quad (1)$$

In each calendar quarter q, we estimate regression (1) using Compustat firm-quarter data with fiscal quarters ending in [q–5, q–2]. We use four quarters of past quarterly data to

[13] Our conclusions remain unchanged if we begin our sample in Q2:1990.

[14] In robustness tests, we also estimate cost stickiness based exclusively on SG&A and total operating costs (Compustat dataitem *xoprq*, as in Banker and Byzalov 2014), and our inferences remain unchanged.

address potential complications due to seasonality, which affects many businesses. Using fiscal quarters up to quarter q–2 instead of q–1 ensures that the β coefficients could have been estimated at the time SPF panelists are preparing their forecasts for submission.[15] The indicator variable $I\_Decrease_{i,q}$ takes a value of 1 if seasonal change in quarterly sales (sales reported in the current quarter compared to four quarters ago) is negative and 0 otherwise.[16] The degree of aggregate cost stickiness exhibited in a given quarter is captured by the magnitude of a negative β_2 coefficient. We multiply the β_2 coefficient estimated in each quarter by –1 so that a larger value indicates greater cost stickiness.[17] Additional data sources for our control variables are described in Section 3.1.1. We align all variables used in the forecasting models so that, at the time forecasts are made, the values of the variables in the models are the most recently available ones. Thus, when forecasts are made in quarter q, for accounting-based variables (including cost stickiness) Compustat data up to quarter q–2 are used (as described above), whereas for other variables that are available on a more timely basis, such as stock market data and certain macro variables, we use values as of the beginning of the month in which forecasts are made.

[15] Form 10-Q filing deadlines are either 40 or 45 days after the fiscal period ends, depending on whether the filer is a large accelerated, accelerated, or non-accelerated filer. Since the SPF survey submission deadline is the middle of the second month of each quarter, it is unlikely that all survey respondents will have had a chance to take into account all of the filings due around that time. In untabulated tests, we relax this condition and use quarterly data up to $q–1$. The estimated coefficients for cost stickiness corresponding to Table 3 are still statistically significant and negative, and the magnitudes of the coefficients are higher for all forecast horizons, consistent with higher predictive power of more timely information.
[16] Alternatively, cost stickiness can be estimated using an annual version of equation 1 in which rolling sums of the past four quarters are used for sales and costs. However, doing so would not allow us to exploit the granularity of cost behavior in individual quarters, and could therefore potentially generate noisier estimates of cost stickiness. In untabulated analysis, we implement this alternative design based on annual changes in sales and costs, and we find that the effect is in the same direction (i.e., higher stickiness is associated with a reduction in unemployment), but is no longer statistically significant.
[17] There are alternative ways of constructing cost stickiness measures based on the estimated coefficients from the cross-sectional regressions. We also calculate aggregate cost stickiness by forming the ratio $(\beta_1+\beta_2)/\beta_1$ and the conclusions we reach are not sensitive to the measure used.

2.1. Descriptive Statistics and Validation Test

2.1.1. Descriptive Statistics

Panel A of Table 1 reports descriptive statistics for the main variables used in the analysis. The historical unemployment rate, expressed as a percentage of the total labor force (individuals who are unemployed but actively seeking employment and willing to work) ranges from 3.90% to 9.93%, with a mean of 6.14%.

The estimated β_1 and β_2 coefficients from the quarterly cross-sectional cost stickiness regressions specified by equation 1, estimated for all Compustat firms, have means of 0.60 and –0.13, respectively. Therefore, for a given quarter, firms report an average increase of 0.60% in their operating costs for every 1% increase in sales revenue, whereas firms report a cost decrease of only 0.47% (0.60% – 0.13%) per 1% decrease in sales revenue.

We next present statistics for the four sets of control variables that we utilize in our analyses (all variables are defined in Appendix A). The first set of control variables captures the overall state of the economy and includes advance GDP ($AdvGDP_t$), aggregate GAAP earnings ($Earn_t$), change in earnings ($\Delta Earn_t$), stock market return ($MktRet_t$), and the industrial production index (IPI_t). The advance estimate of real GDP growth ($AdvGDP_t$) is the first estimate officially released by the Bureau of Economic Analysis during quarter *t* of actual real GDP growth for the most recent quarter t–1, as would have been available to panelists at the time they submit their forecasts to the Philadelphia Fed. Including this control allows us to account for Okun's Law, the robust negative association between unemployment rate and real GDP that is well documented in the literature (e.g., Okun 1963; Kaufman 1988; Ball, Leigh, and Loungani 2013). Over our sample period, this variable ranges from –6.14%

to 7.15% (representing quarter-on-quarter growth in real output, annualized) and has a mean of 2.49%. We also control for aggregate earnings ($Earn_t$), change in earnings ($\Delta Earn_t$), and stock market return ($MktRet_t$) because prior research documents that macroeconomic forecasts do not fully incorporate information contained in aggregate earnings (Konchitchki and Patatoukas 2014). The industrial production index (IPI_t), published by the Federal Reserve Board, measures the real output of all manufacturing, mining, and electric and gas utility establishments in the U.S.

To mitigate concerns that our results may be driven by some innate factors that are correlated with the change in unemployment rate and aggregate cost stickiness, we include a second set of controls which are proxies for the different explanations of cost stickiness discussed in Section 2.2: (a) *BBD* Economics Policy Uncertainty Index ($Uncer_t$), which captures the level of uncertainty (Baker, Bloom, and Davis 2014; Bloom 2014). The index is likely to be correlated with uncertainty about future activities, a potential driver of cost stickiness; (b) The University of Michigan Consumer Sentiment Index (CSI_t). This index gauges consumers' level of optimism or pessimism, which is likely to be correlated with managers' level of optimism or pessimism, another potential explanation for cost stickiness.

The third set of controls includes factors that have been proposed in prior literature as predictors of unemployment specifically (rather than of the macroeconomy as a whole), consisting of labor-force flows and labor reallocations. [18] The 4-week average change in initial unemployment insurance claims (UIC_t) (people who filed for unemployment benefits for the first time during the previous month) and the composite Help-Wanted Index (HWI_t)

[18] Lilien (1982) and Davis (1987) argue that unemployment is, in part, the result of worker turnover from declining to expanding sectors of the economy. Due to labor reallocation frictions related to job search, retraining, or physical relocation, changing jobs takes time, which leads to higher unemployment in the interim. High performance dispersion implies that some firms lay off employees while others recruit new workers.

(number of job openings or vacancies) are proxies for labor flows, often used in policymaking (Barnichon 2010). Employment growth dispersion (Lilien 1982) and return dispersion (Loungani, Rush, and Tave 1990; Brainard and Cutler 1993; Nallareddy and Ogneva 2017) are proxies for performance dispersion.

Our final set of control variables includes federal funds (i.e., interest) rate (IR_t) and inflation rate (Inf_t), following Taylor's (1993) rule as implemented in the SW model.

Panel B of Table 1 presents the correlation matrix among the variables used in our analysis. There is a negative and significant unconditional correlation of –0.30 between aggregate cost stickiness and change in unemployment rate. Change in unemployment rate is positively correlated with return dispersion. In addition, cost stickiness is correlated with several control variables in line with the explanations discussed in Section 2.2. Cost stickiness is positively correlated with advance GDP, consistent with the forward-looking information contained in cost stickiness. It is negatively correlated with the uncertainty index (demand-uncertainty explanation), and positively correlated with consumer sentiment (managerial optimism and pessimism explanation for cost stickiness).

2.1.2. Validation Test

We assess the validity of aggregate cost stickiness by examining its relationship to changes in headcount employed by the firms in the sample (Compustat dataitem *emp*). For each calendar quarter, we calculate the change in total headcount for all firms for which non-missing values of *emp* are available for the current quarter and four quarters ago.

Table 2 shows that there is a significant positive association between currently observed cost stickiness and future reported headcount changes up to four quarters in the future. In order to facilitate interpretation of economic significance in these in-sample results, we normalize the raw cost stickiness variable ($-\beta_2$) by subtracting the sample mean value and dividing by the standard deviation. (Note that, in all out-of-sample tests, we use the raw, non-normalized estimates of cost stickiness obtained by regressing equation (1) over rolling windows as described in section 4.1.2.) Using the normalized variable for cost stickiness, we can interpret the estimated coefficients as follows. For example, the second column of results shows that a one-standard-deviation-greater level of aggregate cost stickiness is associated, one quarter later, with an increase in headcount of 1.35% for the firms in our sample.[19] For longer horizons, the coefficient of cost stickiness and its significance level (and the adjusted *R*-squared) gradually decline, suggesting that the explanatory power of aggregate cost stickiness dissipates with time. Overall, the results in Table 2 provide validation for interpreting the measure as being reflective of labor market conditions.

2.1.3. Univariate Relationship

As preliminary evaluation of the predictive information in aggregate cost stickiness about future unemployment rate, we plot Figure 1 showing the co-movement of the two variables over the business cycle. Aggregate cost stickiness appears to lead the rate of unemployment.

[19] We normalize the raw value of cost stickiness, $-\beta_2$, by subtracting the sample mean (-0.129, Panel A of Table 1) and dividing by the standard deviation (0.040). Scaling an independent variable by a constant, p, will scale the slope coefficient by $1/p$; subtracting a constant from an independent variable does not change the slope coefficient but reduces the intercept by the slope coefficient multiplied by that constant. There is no change to the remaining regression coefficients, any of the t-statistics, or R-squared (See Greene (2012) p. 86-87: "Linearly Transformed Regression"). It is possible to convert the results reported in Table 2 to the results of a regression using the raw values of cost stickiness. Dividing the regression coefficients of cost stickiness in Table 2 by 0.040 gives -38.10, -33.75, -33.80, -29.80, and -26.42 for horizons $t+0$ to $t+5$ respectively (the coefficients obtained when running these regressions with the raw (non-normalized) value of cost stickiness). The corresponding intercepts for regressions using the raw cost stickiness variable are 10.67, 10.03, 10.02, 9.42 and 9.00. For example, for $t+0$, the intercept coefficient can be calculated as: $5.75+38.10\times0.129=10.67$. We use normalized versions of the cost stickiness variable in the in-sample tests (using data over the entire sample period) in order to facilitate comparison of economic effects when estimating cost stickiness using different methods or different subsamples.

3. Forecasts of Unemployment Rate

3.1. OLS Regression Model

3.1.1. In-Sample Prediction

We run an OLS regression, which allows for the inclusion of a battery of indicators. Additionally, the evaluation of incremental predictive ability of cost stickiness is straightforward. We estimate the following OLS regressions:[20]

$$ChUR_{t+k} = \alpha_{1k} + \alpha_{2k}\, CostStickiness_t + \boldsymbol{\alpha}\, \boldsymbol{Controls_t} + \varepsilon_{t+k}, \qquad (2)$$

where $CostStickiness_t$ is estimated in the current quarter using data from public filings made in previous quarters by listed U.S. firms. $ChUR_{t+k}$ is future unemployment rate change for quarter $t+k$. We calculate change in unemployment over different horizons using a similar approach to the Philadelphia Fed (the difference between future unemployment rate in quarter $t+k$ and the most recent estimate of unemployment rate for quarter t–1 available in the middle of quarter t). Because the unemployment rate for quarter t, is not available until quarter t+1, we also include a forecast horizon of 0, which is commonly referred to as "nowcasting". To facilitate economic interpretation, we use annualized measures for change in unemployment.

SPF panelists submit their forecasts around the middle of each quarter. In order to avoid look-ahead bias, we require that the value of aggregate cost stickiness and the values of the control variables be available at the beginning of the forecast month (i.e., the second month of the

[20] We use the OLS regression for forecasting purposes and not to demonstrate a causal relationship between cost stickiness and unemployment rate. The difference between the two contrasting objectives when using an OLS regression is discussed in, e.g., Allison (1999).

quarter). We carefully align the variables used in the analysis according to this timeline. In particular, aggregate earnings and earnings-change variables are fully aligned with the cost stickiness variable, as they are all extracted from firms' financial statements, whereas stock-market-based variables are available on a timelier basis and therefore we use values as of the beginning of the second month of the quarter. For macroeconomic variables, we use the values that are available at the beginning of the second month of each quarter. We apply the Newey-West procedure in order to obtain consistent standard errors in the presence of autocorrelation. We use a truncation parameter (or lag) of 3.[21]

Table 3, Panel A presents the results for future unemployment rate changes observed over the current and following four quarters. For all forecast horizons, consistent with our prediction, we obtain a negative association between cost stickiness and future change in unemployment rates. The coefficients are both economically and statistically significant. For example, for one-quarter ahead (t+1), a one-standard-deviation-higher aggregate cost stickiness is associated with a reduction of 23 basis points in the change in unemployment rate (the dependent variable, unemployment rate change, is measured in percentage points). This effect is economically significant, given that the model includes all the other determinants of cost stickiness and the mean unemployment rate during the sample period is 6.14%. The coefficient for cost stickiness declines in magnitude as we move further into the future (as we would expect).

The coefficients on control variables capturing the state of the overall economy ($AdvGDP_t$, $Earn_t$, $\Delta Earn_t$, $MktRet_t$) are all negative and mostly significant. This pattern is in line with

[21] The choice of 3 lags is based on the usual rule of thumb: $T^{0.25}$, where T is the number of observations. In our sample of 115 quarterly observations, this suggests a truncation parameter of 3. In robustness tests, we allow for different lag lengths and our conclusions remain unchanged.

our expectations and further demonstrates the robustness of Okun's Law. IPI_t does not load for the current and one-quarter-ahead horizon. The coefficients on $Uncer_t$ and CSI_t are also negative and somewhat significant depending on the horizon, consistent with greater optimism being accompanied by reductions in unemployment. $RetDisp_t$ is strongly positive, consistent with labor reallocation frictions resulting in short-run increases in unemployment (Loungani, Rush, and Tave 1990). Likewise, the positive coefficients obtained for IR_t indicate a rise in unemployment following an interest-rate hike, consistent with Stock and Watson (2001).

Overall, the results in Table 3, Panel A lend strong support to the incremental in-sample predictive ability of *CostStickiness* for future unemployment changes beyond other variables studied in prior literature.

3.1.2. Out-of-Sample Prediction

In order to avoid the look-ahead bias inherent in the in-sample prediction, we next perform an out-of-sample analysis. We estimate the predicted change in unemployment rate from model (2) incorporating cost stickiness for an initial period of 10 years beginning in Q1:1985.

$$PrChUR_{t+k} = \hat{\alpha}_{1k} + \hat{\alpha}_{2k}\, CostStickiness_t + \boldsymbol{\hat{\alpha}}\ \boldsymbol{Controls_t} \tag{3a}$$

We conduct the out-of-sample analysis by forecasting at monthly frequencies.[22] We use monthly vintages of employment and unemployment data from the Federal Reserve Bank of St Louis. We ensure that all independent variables are observable before the actual change in unemployment. For financial statement information, which are only available on a quarterly

[22] This is the convention in the macroeconomics literature and used, for example, by Barnichon and Nekarda (2012). We follow this approach to enable comparability of our results to prior research and also across the different models that we examine.

basis, we use the most recent available information as of the middle of each forecasting month, while other macroeconomic variables are updated on a monthly basis when available. In the out-of-sample tests, we do not normalize the cost stickiness variable in order to avoid any look-ahead bias.

By rolling forward the estimation period, one month at a time, we generate a series of out-of-sample forecasts for future changes in unemployment rate over each of the forecast horizons. To back out the level of unemployment rate, we add back the predicted change in unemployment to the actual unemployment rate for quarter *t–1* as observed at time *t*:

$$PrUR_{t+k} = UR_{t-1} + PrChUR_{t+k} \tag{3b}$$

To obtain a quarterly forecast, we follow the macroforecasting literature and we average out the three monthly forecasts generated for each calendar quarter. Since the SPF forecasts are compiled only once per quarter, we align the models' forecasts to generate quarterly-level forecasts using the forecasts produced in the middle of the second month of each calendar quarter.

We compare forecasts for a given calendar quarter to the actual realized unemployment rate (*ex-post*) and we calculate the root-mean-squared-error (RMSE) for each forecasting model. We assess the incremental predictive ability of cost stickiness by comparing the models' RMSEs to a benchmark model—an identical model that does not include cost stickiness. To examine whether the difference in RMSEs between the two models is statistically significant, we apply the methodology in Clark and West (2007).[23]

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[23] Clark and West (2007) compare the forecasting performance of a candidate model to a benchmark model by calculating the following statistics: $CW_t = (UR_t - PrUR\_Bench_t)^2 - [(UR_t - PrUR_t)^2 - (PrUR\_Bench_t - PrUR_t)^2]$, where UR_t is the actual unemployment rate for quarter *t*, $PrUR_t$ is the predicted value under the candidate model, and $PrUR\_Bench_t$ is the predicted value according to the benchmark model. A positive value for CW_t implies that the candidate model has lower RMSE than the benchmark model.

The first row of Table 3, Panel B shows RMSEs for the benchmark model without cost stickiness across the different forecast horizons examined. As expected, longer horizons involve greater uncertainty, thereby generating larger prediction errors. The second row shows the corresponding RMSEs for the model with cost stickiness as an additional predictor variable. The figures in brackets underneath the RMSE's are *p*-values for the *CW* statistics to compare the RMSEs across the two models (without and with cost stickiness). We find that across all forecast horizons, the RMSEs produced by the model with cost stickiness are lower than those of the benchmark model. The greatest improvement in RMSEs due to the inclusion of costs stickiness is in the one-quarter ahead horizon: an improvement of 6.57% (=0.313/0.335 – 1), statistically significant at the one percent level. This improvement dissipates over time.

The third row of the table repeats the out-of-sample prediction tests, with the *CostStickiness* variable being estimated using a subsample of labor-intensive firms. In labor-intensive firms, cost stickiness is more likely to capture workforce-related decisions. Hence, we expect aggregate cost stickiness of labor-intensive firms to be a stronger predictor of the change in unemployment rate. We classify a firm as labor-intensive if the ratio of the number of employees to sales is above the median value in a given quarter.[24] We run equation 1 for labor-intensive firms to generate an alternative set of *CostStickiness* estimates and we use this version of cost stickiness in the third row. Across all forecast horizons, the RMSEs are lower than the corresponding RMSEs for the model using the broader measure of cost stickiness, and we observe an even greater outperformance compared to the benchmark

[24] Firms report number of employees only annually and not all firms report these data. We backfill for fiscal quarters 1 to 3 when the information is available.

model without cost stickiness.

3.2. Vector Autoregression (VAR) Model from Stock and Watson (2001)

Next, we run a vector autoregression (VAR) model, a generalization of a single-variable time-series autoregression (AR) model. Unemployment rate is modeled as a function of other variables in the system and their lags in addition to its own lags, which allows for analysis of the effects of shocks to one or more variables in the system (e.g., Sims 1980a, 1980b; Blanchard and Watson 1986). We build on Stock and Watson (2001), who estimate a VAR model in which the evolution of the unemployment rate follows Taylor's (1993) rule, which stipulates how much the central bank should change the nominal interest rate in response to changes in inflation, output, or other economic conditions. The SW model substitutes growth in output for growth in unemployment, based on Okun's Law. We add to their system our main variable of interest—aggregate cost stickiness—and we estimate the following recursive VAR system:

$$AZ_t = \phi Z_{t-k} + \varepsilon_t, \tag{4}$$

where $Z_t = \left(Inf_{t,}\, UR_{t,} IR_{t,}\, CostStickiness_t\right)'$ is a vector of variables that includes (in this order) inflation (*Inf*), unemployment rate (*UR*), federal funds rate (*IR*), and cost stickiness (*CostStickiness*).

Table 4, Panel A shows the orthogonalized impulse-response graph for the impact of an exogenous shock to *CostStickiness* on unemployment rate. The graph indicates that a one-standard-deviation shock to cost stickiness leads to a reduction in unemployment of 22 basis points. The shock persists (i.e., is reliably negative within a 95% confidence band) for up to 10 quarters.

In out-of-sample analysis, we run the SW VAR model using 10-year rolling windows and apply the estimated coefficients to calculate forecast values of UR_t for horizons of up to four quarters. As before, we compare RMSEs of the forecasts from the VAR systems with and without cost stickiness. The RMSEs in Panel B of Table 4 are larger than the corresponding OLS RMSEs in Table 3. This is not surprising because the SW VAR model involves estimation of many free parameters, which in turn increases the potential for measurement error and hence reduces the overall accuracy of VAR out-of-sample predictions (Clark and West 2007). In addition, the variables incorporated in the SW VAR are also included in the OLS model.

The first row of the table reports the RMSEs from the SW model excluding cost stickiness. The errors of the model incorporating cost stickiness, in the second row of the table, are smaller up to three quarters ahead, and the difference is statistically significant up to two quarters ahead. The improvement in RMSEs in economically significant and ranges from 6.9% to 16.4%. For example, for one-quarter ahead, the improvement in RMSEs after including cost stickiness is 6.9% (=0.365/0.392 – 1), statistically significant at 5% level.

The third row uses cost stickiness estimated for labor-intensive firms. The improvement when using this version of cost stickiness is even larger and ranges from 10.5% to 19.3%.

3.3. Vector Autoregression (VAR) Model from Barnichon and Nekarda (2012) Based on the Inflows and Outflows to Unemployment

The next approach uses a different VAR analysis that forecasts the rates of inflows and outflows to unemployment (i.e., the probabilities that an employed worker becomes unemployed and that an unemployed worker finds a job), and then plugs these flow estimates into a law of motion for unemployment to produce unemployment rate forecasts. This forecasting approach was introduced by Barnichon and Nekarda (2012). A preliminary step to estimating this model is to estimate the flow rate probabilities. We describe this procedure in more detail in appendix B.

Under the BN VAR approach, the vector of variables is:

$Z_t = \left(ln\ s_{t,} ln\ f_{t,} \Delta\ ln\ u_{t,} ln\ uic_{t,} \Delta\ ln\ hwi_t, CostStickiness\right)'$, where s_t is the rate at which employees who begin period *t* employed lose their job during the period, and f_t is the rate at which employees who begin period *t* unemployed find at least one job during the period.

Table 5, Panel A presents the orthogonalized impulse-response graphs for an exogenous shock to *CostStickiness* on unemployment rate. To allow for easy interpretation, we transform the variables from a log basis to a percentage basis in the graphs. The impulse-response graph indicates that a one-standard-deviation exogenous shock to cost stickiness leads to a reduction in unemployment of approximately 5 basis points that persists for 4 quarters.

Next, we examine the out-of-sample performance of the BN model. Compared to the SW model, the BN model produces better forecast in each of the horizons, due to its use of workforce flows. Panel B compares the BN model without and with cost stickiness. The first two rows indicate that adding cost stickiness significantly reduces the RMSEs up to three quarters ahead, by between 10.0% and 14.6%. For example, for one-quarter ahead the reduction is of 11.0% (=0.268/0.301 – 1), significant at the 5% level. When we use cost stickiness estimated for labor-intensive firms (third row), the reduction in RMSEs ranges from 11.1% to 18.0%.

3.4. Professional Forecasters

In this section, we examine whether SPF panelists consider cost stickiness when making their forecast. To do so, we compare the RMSEs of prediction models incorporating cost stickiness to the SPF forecast errors. The test of RMSEs improvement is a joint test of both the unemployment prediction model and the inclusion of cost stickiness. To take advantage of the different information sets exploited by each of the models examined, we first combine their forecasts by applying weights (determined using OLS regressions in a dynamic fashion and using available history only). Forecast combination is commonly used in the macroeconomics forecasting literature (see e.g., Bates and Granger 1969; Wright 2008).[25]
The first row of Table 6, Panel A presents the RMSEs of the SPF forecasts, while the second and third rows present the RMSEs of the combined forecasts from models without and with cost stickiness. Comparing combined forecasts from models excluding cost stickiness to the

[25] To assign weights for the forecasts produced by the individual models, we follow Barnichon and Nekarda (2012) and run an OLS regression of actual unemployment rate on the forecasts from the three models using past data only. We then use the resulting regression coefficients as weights applied to the individual models' forecasts produced in the current quarter. Because the BN VAR outperforms the SW VAR across all forecast horizons, we only consider the former in the forecast combination.

SPF forecasts, we find statistically significant improvement in RMSEs up to one quarter ahead. Yet, combined forecasts from models including cost stickiness have lower RMSEs and outperform the SPF mean consensus forecasts up to two quarters ahead.[26] The final row of Table 6, Panel A shows the RMSEs when using cost stickiness estimated using labor-intensive firms. This model also outperforms the SPF forecasts up to two quarters ahead. Collectively, these findings suggest that SPF panelists tend to overlook at least some of the information contained in cost stickiness, and that incorporating this information improves forecast performance.

3.4.1. SPF Panelists' Industry

We next consider the industry in which SPF panelists are employed. As discussed in Section 2.1, the panelists work in both financial and nonfinancial industries. We expect panelists from financial industries to have better expertise and/or better access to real-time, economy-wide financial statements data (for example, through costly subscriptions to financial databases), relative to their counterparts from nonfinancial industries. Hence, these panelists are more likely to incorporate cost stickiness into their forecasts.

To test this conjecture, we collect information about the industry of the firm employing the SPF panelist, and note their classification as financial or nonfinancial.[27] We calculate consensus mean forecasts and RMSEs for the two groups of panelists in each quarter. Table 6, Panel B reports the results: the first row presents the RMSEs of combined forecasts from models with cost stickiness (as in Panel A). We then compare these to the RMSEs of forecasts

[26] In untabulated results, we use median consensus forecasts as an alternative, and our conclusions continue to hold.

[27] This classification is provided by the Philadelphia Fed. The Philadelphia Fed also includes a third classification ("unknown") which we omit from this analysis.

from the two groups of SPF panelists. Across all forecast horizons, the RMSEs of forecasts by panelists from nonfinancial industries are larger. Furthermore, the combined forecasts from models with cost stickiness outperform the forecasts of panelists from financial industries up to one quarter ahead and the forecasts of panelists from nonfinancial industries up to two quarters ahead.

This evidence suggests that both groups of panelists overlook at least some of the information contained in cost stickiness. Moreover, it appears that forecasters who are employed in financial industries tend to overlook this information to a lesser degree than panelists in nonfinancial industries. For horizons above two quarters, SPF forecasts have lower RMSEs than the combined models' forecasts. Interestingly, in the special survey on forecast methods conducted by the Philadelphia Fed in 2009, panelists' responses indicate a decreasing reliance on models (structural and/or time series) for longer forecast horizons, for which they prefer to rely on their intuition and expertise. Overall, the findings are consistent with these survey responses.

4. Additional Analyses

We examine whether the relationship between cost stickiness and future unemployment rate is stronger when considering subsamples of firms or time periods. For ease of interpretation, we present the next set of results using a normalized measures of cost stickiness and in-sample OLS regressions instead of the VAR approach for the following reasons. The VAR approach takes into account time-series interdependencies of the different macroeconomic variables of interest. One major disadvantage of VAR models, however, is the need to estimate a very large number of coefficients (Robertson and

Tallman 1999). Compared to OLS approaches, the number of cross-sectional predictors that a VAR model can handle is relatively limited because the number of coefficients to be estimated grows exponentially with the number of variables. This can hurt the accuracy of the parameter estimates and hence of the forecasts given by the model. Instead of the VAR results, we decide to present the more stable OLS estimates and some of these coefficients may not have any significant effects on the dependent variable.

We run variations of OLS model 2 in which we decompose the *CostStickiness* variable or interact it with other variables of interest. For brevity, we report in the tables only the main coefficients of interest and suppress presentation of the intercepts and control variables other than *AdvGDP* (to assess the robustness of Okun's Law).

4.1. The Predictive Power of Cost Stickiness in Recessionary Periods

We evaluate the forecasting improvement of cost stickiness during recessions, when predicting unemployment rate is particularly difficult. It has long been known that increases in the unemployment rate at the onset of recessions are much sharper than declines when recovery takes place (e.g., Neftci 1984; Falk 1986; Sichel 1989; Montgomery, Zarnowitz, Tsay, and Tiao 1998).

We expect that the predictive power of cost stickiness will be stronger towards the end of a recessionary period than at the start. At the onset of a recession, a larger proportion of firms experience a reduction in sales and, to improve their margins, they cut costs back more steeply as sales fall (Banker, Fang, and Mehta 2012). Hence, their cost behavior becomes "anti-sticky"—that is, the opposite of the on-average sticky cost behavior during normal economic times (Weiss 2010). At these points of the business cycle, the high proportion of firms with anti-sticky behavior reduces the information content of aggregate cost stickiness for the entire sample. In contrast, towards the end of a recession, after employers have endured the effects of the downturn, they tend to retain slack resources in anticipation of sales recovery (including those that experienced sales decreases), thus leading to cost stickiness. Hence, we expect the informativeness of cost stickiness to be greater upon recovery from a recession.

To test this conjecture, we repeat the analysis in Panel A of Table 3 and interact cost stickiness with two indicator variables, for the beginning and end of recessionary periods. Table 7, Panel A shows that, towards the end of recessions, cost stickiness improves unemployment forecasts up to three quarters ahead. In untabulated results, we conduct a similar analysis using the BN model and observe similar patterns.

Panel B repeats the analysis in Table 3, Panel A after dropping the financial crisis (observations from Q4:2007 to Q1:2009). The financial crisis was the most severe downturn since the Great Depression and resulted in a 5% increase in unemployment in the U.S., as depicted in Figure 1.[28] The coefficients on cost stickiness are only slightly attenuated compared with the coefficients reported in Table 3, Panel A, i.e., the results are robust to excluding the crisis period. Formal statistical tests (untabulated) confirm this to be the case.

4.2. Cross Sectional Analyses

[28] See also NBER report: http://www.nber.org/bah/2010no3/w16407.html

4.2.1. Governance Effect

We next consider the effect of agency problems. As discussed in Section 2.2, agency problems can lead to higher cost stickiness for reasons unrelated to economic factors. This could, in turn, bias the estimate of cost stickiness upward and confound its predictive ability. We therefore expect stronger predictive ability in firms with fewer agency issues.

We use the *BCF* Entrenchment Index from Bebchuk, Cohen, and Ferrell (2009) to proxy for the severity of agency problems.[29] We classify a firm as having strong (weak) governance if its *BCF* Entrenchment Index is above (below) the median value. We then estimate cost stickiness for each of these groups separately, and then re-estimate equation 2 by including the two cost stickiness variables as independent variables. Table 8, Panel A shows that the predictive power of cost stickiness is entirely driven by the strong governance group. In terms of economic significance, for one quarter ahead, for example, a one-standard-deviation-higher cost stickiness observed in the strong governance group is associated with a 35 basis points decrease in unemployment rate. This economic effect is one and a half times the effect of cost stickiness when it is calculated for all firms as shown in corresponding column in Table 3, Panel A. A similar pattern holds for the other horizons examined.

4.2.2. Asset Intensity

The next test concerns asset-intensive firms. We conjecture that cost stickiness estimated for asset-intensive firms has lower predictive power because, in these firms, cost stickiness is likely to capture asset-related adjustment costs, while labor-adjustment costs will be reflected

[29] This index is based on six provisions: staggered boards, limits to shareholder bylaw amendments, limits to shareholder charter amendments, supermajority requirements for mergers, poison pills, and golden parachutes.

less prominently. Panel B shows that, as expected, the predictive ability of cost stickiness is driven by low-asset-intensive firms.

4.2.3. Industry Concentration

Prior literature has examined whether the cyclicality of real marginal cost varies with industry concentration.[30] To test empirically the impact of industry concentration in our setting, we create two subsamples of firms with low and high industry concentration, using the Herfindahl-Hirschman Index (*HHI*) of the firms' sales. We then estimate cost stickiness separately for the two subsamples. The results, presented in Panel C, show higher predictive power for cost stickiness of firms in more highly concentrated industries.

4.3. Alternative Cost Stickiness Estimation Procedures

In this section, we assess the generalizability of our results to alternative cost stickiness estimation procedures. The first alternative is proposed by Weiss (2010), who introduces a firm-quarter level measure of cost stickiness ($Sticky_{i,t}$, see appendix A). To allow a higher value of $Sticky_{i,t}$ to correspond to more sticky cost behavior, we multiply Weiss's (2010) original measure by –1. We then aggregate the measure by using equal-weighted cross-sectional averages of all available firms.[31] Compared to the more parsimonious approach using regression 1, Weiss's methodology includes only firms that experienced both an

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[30] Domowitz, Hubbard, and Petersen (1986) find that the real marginal cost in concentrated industries is countercyclical: It falls in booms and rises in recessions (see also Qualls 1979). Yet, the real marginal cost in unconcentrated industries tends to be procyclical: It rises in booms and falls in recessions. The authors argue that their finding of countercyclical marginal cost in concentrated industries is due to higher cost rigidity (specifically, real-wage rigidity) in these industries. At the same time, Bils (1987) finds no effect of concentration on the relationship between the business cycle and the real marginal cost.

[31] Our inferences remain the same if we construct the aggregate accounting earnings series using value-weighted averages, with weights based on market capitalization as of the beginning of the quarter.

increase and a decrease in sales during the previous four quarters. A potential advantage of including only these firms is that they may be more sensitive to the macroeconomy. On the other hand, it also entails loss of observations. For our sample period, approximately half of the distinct firms on Compustat do not have an estimate of $Sticky_{i,t}$ in any given quarter. A second alternative approach follows Balakrishnan, Labro, and Soderstrom (2014), who propose a linear model to estimate cost stickiness (see appendix A). Panels A and B of Table 9 present the results of estimating equation 2 with those two alternative measures. We normalize both measures in order to facilitate comparison of effects across the different measures. We find a negative and significant relationship between aggregate cost stickiness and future unemployment rate across all horizons for the Weiss (2010) measure. Using the Balakrishnan, Labro, and Soderstrom (2014) measure, we obtain statistically significant results in all quarters except for the current one, albeit with lower *p*-values (and smaller coefficient magnitudes) compared with the Weiss (2010) measure.

4.4. The Predictive Ability of Cost Stickiness beyond One Year

In all of our tests so far, we have focused on the predictive power of cost stickiness up to four quarters ahead. This is because we expect cost stickiness to be informative only in the short term. In untabulated tests, we expand the forecast horizon up to eight quarters ahead. Beginning with five quarters ahead, we find no improvement from including cost stickiness in the OLS regression (both in- and out-of-sample). For the SW and BN models, the improvement from the inclusion of cost stickiness is even shorter, as discussed in section 4.

4.5. Inventory Changes and Business Activity

In line with the existing cost stickiness literature, we have made use of data from firms' income statements to capture the sensitivity of changes in costs to changes in sales. A substantial proportion of our sample firms carry inventory. If firms build up inventory (i.e., produce or purchase more units than they sell), the cost of units sold (i.e., COGS) underestimates production costs or purchases for the current period. Firms are likely to produce to inventory when they experience a negative shock to their demand which they believe to be temporary. In this case, the coefficient estimate for β_2 could be biased. We conduct a robustness test in which we re-run equation (1) by adjusting COGS for changes in inventory during the period, to account for the difference between the cost of units produced or purchased and the cost of units sold as reported on the income statement.

We present the results of this analysis in Table 9, Panel C. The predictive ability of cost stickiness is essentially unchanged: while we lose statistical significance of this cost stickiness measure for horizon *t+4*, coefficient magnitudes and *t*-statistics for all other horizons are very similar to those reported in Table 3, Panel A.

5. Conclusion

In this paper, we have examined the predictive ability of an aggregate measure of cost stickiness when forecasting macrolevel unemployment rates in the U.S., a complex and important task faced by policymakers. We argue that cost stickiness captures firms' decision-making with regard to employee hiring, retention, and termination. Accordingly, cost stickiness constitutes a leading indicator of future macrolevel unemployment rate.

A considerable body of literature—beginning with Anderson, Banker, and Janakiraman (2003)— suggests that the degree of cost stickiness reflects the level of adjustment costs faced by firms and managerial expectations of future activity (Banker and Byzalov 2014). So far, this literature has not examined the predictive power of cost stickiness for the macroeconomy. We use Compustat quarterly data to estimate quarterly values of aggregate cost stickiness. We validate the measure by showing that periods of high cost stickiness (when firms are reluctant to fire employees) are followed by increases in the overall number of employees of these firms.

We then examine three different types of unemployment prediction models and show that incorporating cost stickiness into each model improves its forecasting performance. We examine an OLS regression specification and two VAR models. The first VAR is the SW model, which predicts unemployment based on Taylor's (1993) rule, and the second one is the BN model, which forecasts separately the inflows and outflows to unemployment. In-sample results indicate that cost stickiness is negatively associated with future unemployment rate over multiple quarters. Out-of-sample analysis indicates that including cost stickiness reduces RMSEs of all three classes of models examined. We also show that forecasts generated by combining the models including cost stickiness outperform the SPF forecasts up to two quarters ahead.

In additional analysis, we find that the predictive ability of cost stickiness is greater upon recovery from recessions than at the start. Cross-sectional analysis demonstrates that aggregate cost stickiness has a higher predictive power when estimated for subsamples of firms which: (a) have lower agency problems; (b) have lower capital intensity; and (c) operate in concentrated industries. Finally, we demonstrate the robustness of the findings to alternative empirical measures of cost stickiness that have been proposed in the literature.

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Appendix A

Definitions of key variables

β_1 and β_2 coefficient estimates	Estimated coefficients obtained from running the following ordinary least squares regression cross-sectionally each quarter *t* using Compustat quarterly data for quarters *q* in [*t*–*5*, *t*–*2*]: $\log\left[\frac{(COGS+SG\&A)_{i,q}}{(COGS+SG\&A)_{i,q-4}}\right] = \beta_0 + \beta_1 \log\left[\frac{SALES_{i,q}}{SALES_{i,q-4}}\right] + \beta_2 I\_Decrease_{i,q} \log\left[\frac{SALES_{i,q}}{SALES_{i,q-4}}\right] + e_{i,q}$
Aggregate cost stickiness ($CostStickiness_t$)	β_2 coefficient estimates × –1, normalized by subtracting its sample mean and dividing by standard deviation
Historical unemployment rate, actual realization (UR_t)	Civilian unemployment rate as compiled by the Federal Reserve Bank of Philadelphia using data released by the Bureau of Labor Statistics
Change in unemployment rates ($ChUR_t$)	First difference in historical quarterly unemployment rate (UR_t)
Advance estimate of real GDP growth rate ($AdvGDP_t$)	First-release (advance) estimate of real GDP growth rate for quarter *t*–*1* issued during quarter *t*
Aggregate earnings ($Earn_t$)	Equal-weighted average earnings (scaled by contemporaneous sales) available in quarter *t*. We calculate aggregate GAAP earnings each quarter as the cross-sectional equal-weighted averages of earnings (scaled by contemporaneous sales), following the procedure described in Konchitchki and Patatoukas (2014).
Market return ($MktRet_t$)	Equal-weighted average return for our sample stocks available in quarter *t*.
Industrial production index (IPI_t)	Industrial production index from the Federal Reserve Bank of St. Louis
BBD Economic Policy Uncertainty Index ($Uncer_t$)	Economic policy uncertainty obtained from www.policyuncertainty.com website, based on Baker, Bloom, and Davis (2014). This index is constructed from three underlying components—disagreement among economic forecasters, the number of federal-tax-code provisions set to expire in future years, and newspaper coverage of policy-related economic uncertainty.
Consumer Sentiment Index (CSI_t)	Index of consumer sentiment based on surveys of consumers by the University of Michigan. This index is constructed from a national representative survey based on telephonic household interviews and it captures short-term consumer attitudes about the business climate, spending, and personal finance.

4-week average of unemployment insurance weekly claims (UIC_t)	4-week average of unemployment insurance weekly claims released by the U.S. Department of Labor Employment & Training Administration
Help-Wanted Index (HWI_t)	Composite Help-Wanted Index, captures the number of job openings or vacancies
Employment growth dispersion ($EmpGDisp_t$)	Sector-level employment growth dispersion available in quarter *t*, measured as residual from an AR(2) model: $AggEmpGDisp_t = r_0 + r_1\, AggEmpGDisp_{t-1} + r_2\, AggEmpGDisp_{t-2} + e_t.$ where $AggEmpGDisp_{t-k}$ is aggregate employment growth dispersion estimate for quarter $t-k$. (See Nallareddy and Ogneva 2017).
Stock return dispersion ($RetDisp_t$)	Stock return dispersion available in quarter *t*, measured as the residual from an AR(2) model: $AggRetDisp_t = r_0 + r_1\, AggRetDisp_{t-1} + r_2\, AggRetDisp_{t-2} + e_t.$ where $AggRetDisp_{t-k}$ is aggregate stock return dispersion estimate for quarter $t-k$
Effective Federal Funds rate (IR_t)	Federal funds rate released by the Federal Reserve Bank of New York
Inflation (Inf_t)	Quarterly average of monthly annualized changes in chain-weighted GDP price index, as in Stock and Watson (2001)
Weiss (2010) aggregate cost stickiness	Firm-quarter level measure of cost stickiness ($Sticky_{i,t}$) aggregated across all sample firms: $Sticky_{i,t} = \log\left[\frac{\Delta(COGS + SG\&A)}{\Delta SALES}\right]_{i,\overline{\tau}} - \log\left[\frac{\Delta(COGS + SG\&A)}{\Delta SALES}\right]_{i,\underline{\tau}}$ where $\overline{\tau}, \underline{\tau} \in \{t, \ldots, t-3\}$, and $\overline{\tau}$ ($\underline{\tau}$) is the most recent quarter from the past four quarters in which the firm experienced an increase (a decrease) in sales. The aggregated measure is normalized.
Balakrishnan, Labro, and Soderstrom (2014) aggregate cost stickiness	Estimated β_2 coefficient, obtained from running the following ordinary least squares regression cross-sectionally each quarter *t* using Compustat quarterly data for quarters *q* in [t–5, t–2]: $\frac{(COGS + SG\&A)_{i,q} - (COGS + SG\&A)_{i,q-4}}{SALES_{i,q-4}} = \beta_0 + \beta_1 \frac{SALES_{i,q} - SALES_{i,q-4}}{SALES_{i,q-4}} + \beta_2 I\_Decrease_{i,q} \frac{SALES_{i,q} - SALES_{i,q-4}}{SALES_{i,q-4}} + e_{i,q}$ The coefficient is multiplied by –1 and normalized.

Appendix B
Estimating the inflows and outflows of unemployment

We outline an estimation approach developed recently by Barnichon and Nekarda (2012) which is based on separately forecasting the flows in and out of unemployment (i.e., employed workers becoming unemployed and unemployed workers finding jobs). The starting point is a law of motion for unemployment (Shimer 2005; 2012).

Suppose $u_{t+\tau}$ is the unemployment rate at instant $t + \tau$. t denotes months and $\tau \in [0,1)$ is a continuous measure of time within each month. Assume that, during month t+1, all unemployed persons can find a job according to a Poisson process with arrival rate f_{t+1}, and all employed workers lose or leave their job according to a Poisson process with arrival rate s_{t+1}.

The unemployment rate then evolves according to

$$\frac{du_{t+\tau}}{d\tau} = s_{t+1}(1 - u_{t+\tau}) - f_{t+1}u_{t+\tau,} \tag{B1}$$

(changes in unemployment consist of the difference between inflows and outflows).

Solving equation 1 yields

$$u_{t+\tau} = \beta_{t+1}(\tau)u^*_{t+1} + [1 - \beta_{t+1}(\tau)]u_t, \tag{B2}$$

where

$$u^*_{t+1} \equiv \frac{s_{t+1}}{s_{t+1} + f_{t+1}} \tag{B3}$$

denotes the conditional steady-state unemployment rate, and $\beta_{t+1}(\tau) \equiv 1 - e^{-\tau(s_{t+1}+f_{t+1})}$ is the rate of convergence to that steady state.

Empirically, Barnichon and Nekarda (2012) implement the following procedure. Time-series data are obtained from official sources for *E* (civilian employment level), *U* (unemployment level), and *ULT5* (unemployed less than 5 weeks). Using equation B2—which expresses the relationship between u, s and f—historical time series for u, s, and f can be constructed from those time series data.

In order to produce forecasts, a VAR system is estimated which includes two leading indicators of labor force flows: vacancy postings (proxied by Barnichon's (2010) composite help-wanted index) and initial claims for unemployment insurance (obtainable from the labor department).

$$y_t = \left(ln\ s_{t,} ln\ f_{t,} \Delta\ ln\ u_{t,} ln\ uic_{t,} \Delta\ ln\ hwi_t\right)', \tag{B4}$$

where *uic* is the monthly average of weekly initial claims for unemployment insurance and *hwi* is the help-wanted index.

The forecast values of s and f obtained from running the VAR model in B4 can then be plugged back in equation B2 to produce forecasts of unemployment rate. For forecast horizons beyond one month, the forecasts can be produced by implementing equation B2 recursively. Barnichon and Nekarda (2012) claim that forecasts of u obtained from the law of motion in this manner are superior to those that are produced directly from the VAR system in equation B4, because this method allows for the flows to have different time series properties over the forecast horizon.

Table 1. Descriptive statistics

Panel A: Summary statistics

Variable	Obs.	*Mean*	*SD*	Min.	Median	Max.
Main Variables						
UR_t	116	6.143	1.502	3.900	5.700	9.933
$ChUR_t$	116	–0.005	0.281	–0.467	–0.067	1.400
β_1 coefficient estimates	116	0.604	0.057	0.481	0.596	0.791
β_2 coefficient estimates	116	–0.129	0.040	–0.272	–0.126	–0.031
Control Variables						
$AdvGDP_t$	115	2.49	1.96	–6.14	2.46	7.15
$Earn_t$	116	0.02	0.08	–0.40	0.04	0.09
$\Delta Earn_t$	116	–0.15	0.22	–1.55	–0.13	0.19
$MktRet_t$	116	0.03	0.11	–0.30	0.03	0.32
IPI_t	116	83.12	16.06	56.48	90.06	104.94
$Uncer_t$	116	108.24	30.70	63.12	102.27	215.89
CSI_t	116	87.49	12.54	57.60	90.60	112.00
UIC_t	116	0.37	0.06	0.27	0.35	0.66
HWI_t	116	84.96	14.11	58.28	86.61	111.79
$EmpGDisp_t$	116	–0.09	0.41	–1.47	–0.15	1.61
$RetDisp_t$	116	0.00	0.04	–0.10	0.00	0.19
IR_t	116	4.13	2.73	0.07	4.78	9.73
Inf_t	116	2.24	0.95	–0.62	2.11	4.80

Panel B: Pairwise Pearson correlations

	$ChUR_t$	Cost $Stickiness_t$	$AdvGDP_t$	$Earn_t$	$\Delta Earn_t$	$MktRet_t$	IPI_t	$Uncer_t$	CSI_t	UIC_t	HWI_t	EmpG $Disp_t$	Ret $Disp_t$	IR_t
$CostStickiness_t$	**–0.30**													
$AdvGDP_t$	**–0.57**	**0.28**												
$Earn_t$	–0.21	0.15	0.06											
$\Delta Earn_t$	–0.20	0.00	0.19	0.19										
$MktRet_t$	–0.20	0.00	**0.32**	0.02	–0.17									
IPI_t	0.05	–0.15	0.03	**–0.42**	0.15	–0.02								
$Uncer_t$	0.03	**–0.35**	**–0.35**	0.12	–0.19	–0.10	–0.05							
CSI_t	**–0.27**	**0.37**	**0.48**	–0.15	0.09	0.19	–0.17	**–0.65**						
UIC_t	0.15	**–0.26**	**–0.24**	–0.01	**–0.37**	0.15	–0.04	**0.58**	**–0.59**					
HWI_t	–0.04	0.18	0.17	0.01	0.22	–0.14	0.01	**–0.49**	**0.60**	**–0.74**				
$EmpGDisp_t$	0.22	–0.06	–0.13	–0.04	**–0.30**	0.07	–0.08	0.18	–0.11	**0.28**	–0.12			
$RetDisp_t$	**0.23**	0.04	–0.06	–0.02	–0.11	0.12	–0.06	0.05	0.04	–0.06	0.14	0.14		
IR_t	0.04	0.21	0.08	0.22	0.07	–0.04	**–0.69**	**–0.43**	**0.57**	**–0.43**	**0.60**	–0.01	0.13	
Inf_t	–0.05	–0.06	0.01	0.20	**0.32**	0.01	**–0.34**	–0.23	0.19	**–0.35**	**0.27**	–0.17	0.00	**0.49**

Table shows descriptive statistics for the main variables. The sample consists of 116 calendar quarterly observations ranging from Q1:1985 to Q4:2013. One observation is missing for the advance release of real GDP growth rate for Q4:1995 because of a government shutdown. Variables are as defined in Appendix A. Panel A shows summary statistics for the main variables. Panel B shows pairwise correlations among the independent variables used in the main analyses. Values shown in boldface indicate two-tailed statistical significance at 1% level.

Table 2. Validation of aggregate cost stickiness measure—change in headcount regressions

Change in aggregate headcount$_{t+k}$ = α_{1k} + α_{2k} *CostStickiness*$_t$+ ε_{t+k}

	Forecast horizon (quarters)				
Model	*t+0*	*t+1*	*t+2*	*t+3*	*t+4*
CostStickiness$_t$	1.53***	1.35***	1.36***	1.19**	1.06**
	(3.59)	(3.01)	(2.98)	(2.58)	(2.27)
Intercept	5.75***	5.67***	5.65***	5.57***	5.59***
	(7.66)	(8.43)	(8.69)	(8.33)	(7.94)
Number of quarters	116	116	116	116	116
Adjusted *R*-squared	0.162	0.126	0.126	0.097	0.074

Table reports the results of ordinary least squares regressions of future changes in aggregate headcount on aggregate cost stickiness estimated in the current quarter using public firms' accounting data from previous quarters. Variables are as defined in Appendix A. *t*-statistics shown in parentheses underneath the estimated coefficients are based on Newey and West (1987) heteroskedasticity and autocorrelation-consistent standard errors with three lags. ***, **, and * indicate two-tailed statistical significance at levels 1%, 5%, and 10%, respectively.

Figure 1. Unemployment rate and cost stickiness over time

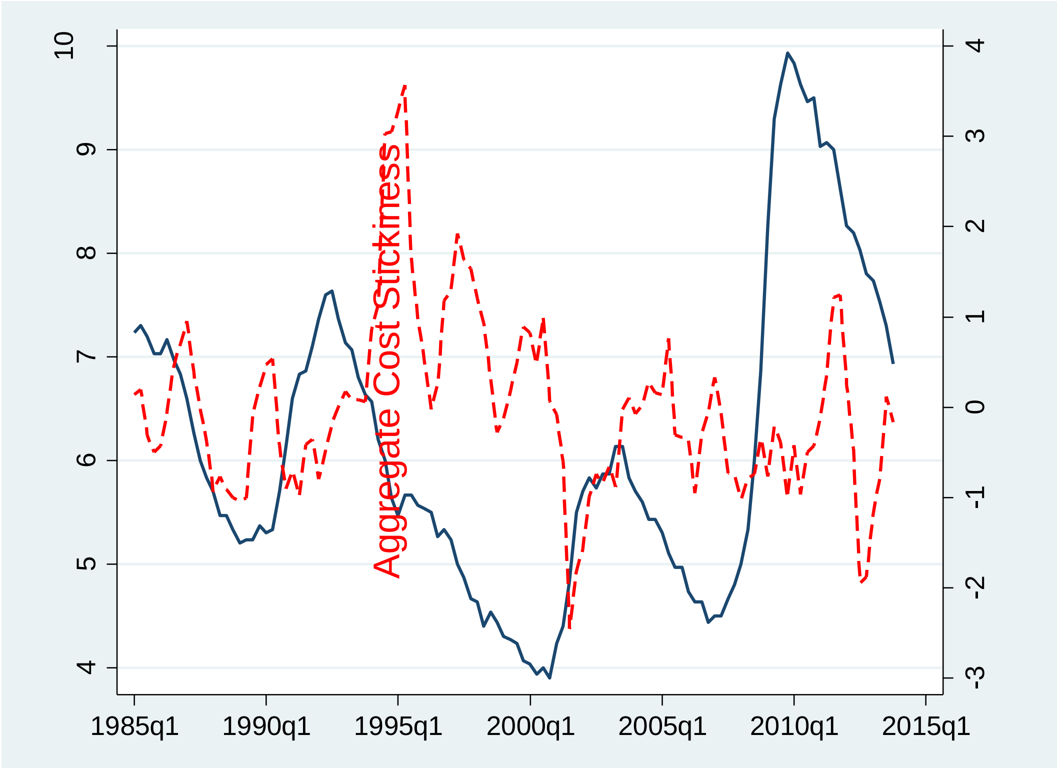


Figure shows macrolevel unemployment rates (in solid line) and aggregate cost stickiness (in dash line) estimated quarterly using public firms for the period 1985 to 2013.

Table 3. Association between aggregate cost stickiness and future unemployment rate –
OLS Regression

$$ChUR_{t+k} = \alpha_{1k} + \alpha_{2k}\ CostStickiness_t + \boldsymbol{\alpha}\ \boldsymbol{Controls_t} + \varepsilon_{t+k}$$

Panel A: In-sample estimation

	Forecast horizon (quarters)				
	t+0	*t+1*	*t+2*	*t+3*	*t+4*
$CostStickiness_t$	–0.255***	–0.231***	–0.173***	–0.141**	–0.120*
	(–3.58)	(–3.38)	(–2.69)	(–2.31)	(–1.98)
$AdvGDP_t$	–0.254***	–0.265***	–0.224***	–0.178***	–0.157***
	(–3.76)	(–3.72)	(–3.84)	(–3.66)	(–3.97)
$Earn_t$	–0.782	–1.220*	–1.451**	–1.762**	–1.709**
	(–0.88)	(–1.79)	(–2.03)	(–2.61)	(–2.38)
$\Delta Earn_t$	–0.992**	–0.487*	–0.356	–0.356	–0.251
	(–2.60)	(–1.73)	(–1.29)	(–1.43)	(–1.05)
$MktRet_t$	–2.196**	–1.320*	–1.509**	–1.393***	–1.174**
	(–2.53)	(–1.90)	(–2.57)	(–2.73)	(–2.27)
IPI_t	0.012	0.014	0.023*	0.029**	0.034***
	(0.96)	(1.08)	(1.85)	(2.55)	(3.11)
$Uncer_t$	–0.013**	–0.013**	–0.011*	–0.01	–0.009
	(–2.50)	(–2.24)	(–1.75)	(–1.65)	(–1.60)
CSI_t	–0.018*	–0.022*	–0.026	–0.032*	–0.032*
	(–1.75)	(–1.70)	(–1.52)	(–1.67)	(–1.66)
UIC_t	2.601	1.509	1.849	0.497	0.131
	(1.39)	(0.92)	(1.17)	(0.32)	(0.08)
HWI_t	–0.025**	–0.017	–0.017	–0.019	–0.019
	(–2.18)	(–1.16)	(–1.07)	(–1.29)	(–1.42)
$EmpG\_Disp_t$	0.423**	0.350*	0.321*	0.27	0.224
	(2.27)	(1.96)	(1.84)	(1.65)	(1.48)
Ret_Disp_t	5.801***	5.308***	5.028***	4.494***	3.977***
	(3.10)	(3.16)	(3.25)	(3.17)	(3.21)
IR_t	0.16	0.167	0.227**	0.274***	0.310***
	(1.60)	(1.48)	(2.08)	(2.78)	(3.49)
Inf_t	–0.153*	–0.175**	–0.104	–0.082	–0.068
	(–1.76)	(–2.07)	(–1.26)	(–0.94)	(–0.76)
Intercept	3.486*	3.457	2.176	2.432	1.817
	(1.68)	(1.70)	(0.99)	(1.03)	(0.80)
Number of quarters	115	115	115	115	115
Adjusted R-squared	0.604	0.642	0.623	0.598	0.584

Panel B: Out-of-sample predictive performance

Model	*Forecast horizon (quarters)* *t+0*	*t+1*	*t+2*	*t+3*	*t+4*
OLS without cost stickiness	0.137	0.335	0.568	0.971	1.350
OLS with cost stickiness	0.132**	0.313***	0.546**	0.970*	1.341*
	(0.036)	(0.007)	(0.050)	(0.058)	(0.100)
OLS with cost stickiness, labor-intensive firms only	0.130**	0.311***	0.534**	0.941**	1.340*
	(0.020)	(0.005)	(0.031)	(0.020)	(0.100)

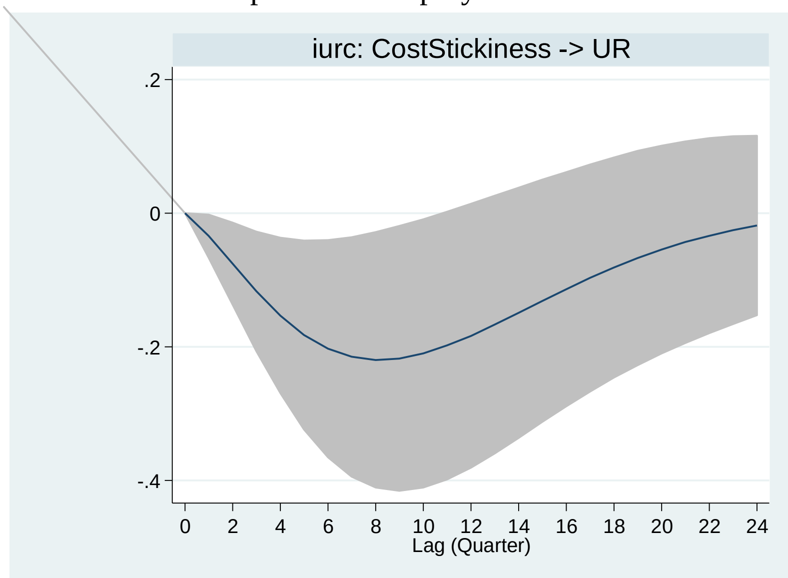
Panel A reports in-sample results of OLS regressions of future macrolevel unemployment rate changes on aggregate cost stickiness estimated in the current quarter, using public firms' accounting data from previous quarters. Variables are defined in Appendix A. *t*-statistics shown in parentheses underneath the estimated coefficients are based on Newey and West (1987) heteroskedasticity and autocorrelation-consistent standard errors with three lags. Panel B presents out-of-sample root-mean-squared-errors (RMSEs) between actual unemployment rate and the forecast values from the regressions presented in Panel A using 10-year rolling windows, with and without the inclusion of cost stickiness. Clark and West (2007) *p*-values to compare the RMSEs across models excluding and including cost stickiness are shown in parentheses below the RMSE values. Two estimations of cost stickiness are shown: using the entire Compustat sample of firms, and using a subsample of labor-intensive firms. Labor-intensive firms are defined as having a ratio of number of employees to sales larger than the quarterly median. ***, **, and * indicate two-tailed statistical significance at levels 1%, 5%, and 10%, respectively.

Table 4. Association between aggregate cost stickiness and future unemployment rate –
VAR model based on Stock and Waston (SW) (2001)

$$AZ_t = \phi Z_{t-k} + \varepsilon_t, \text{ where } Z_t = \left(Inf_{t,}\ UR_{t,} IR_{t,}\ CostStickiness_t\right)'$$

Panel A: Impulse-response graph to shock in aggregate cost stickiness

Response: Unemployment rate



Panel B: Out-of-sample predictive performance

	Forecast horizon (quarters)				
Model	*t+0*	*t+1*	*t+2*	*t+3*	*t+4*
SW VAR without cost	0.176	0.392	0.751	1.419	1.767
SW VAR with cost stickiness	0.147**	0.365**	0.687**	1.416	1.772
	(0.011)	(0.042)	(0.045)	(0.419)	N/A
SW VAR with cost stickiness,	0.142***	0.351**	0.671**	1.379	1.767
labor-intensive firms only	(0.004)	(0.017)	(0.019)	(0.366)	N/A

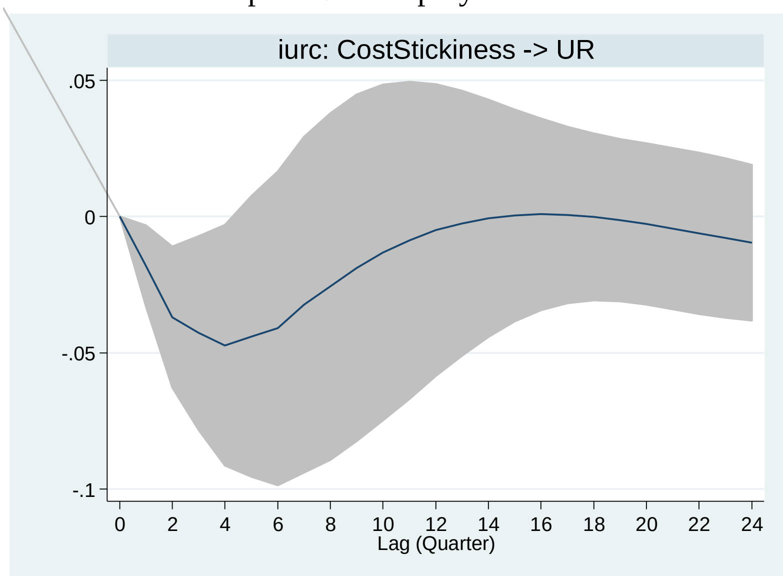
Table reports the results of a VAR model (Stock and Watson 2001) including the following variables: inflation (Inf_t), unemployment rate (UR_t), federal funds rate (IR_t), and aggregate cost stickiness ($CostStickiness_t$). Panel A shows the impulse-response function (IRF) graph for the response of unemployment rate to a one-standard-deviation shock to *CostStickiness.* 95% confidence bands are also presented (shaded areas). Variables are defined in Appendix A. Panel B presents root-mean-squared-errors (RMSEs) between actual unemployment rate and the forecast values from the VAR model presented in Panel A using 10-year rolling windows, with and without the inclusion of cost stickiness. Clark and West (2007) *p*-values to compare the RMSEs across models excluding and including cost stickiness are shown in parentheses below the RMSE values. Two estimations of cost stickiness are shown: using the entire Compustat sample of firms, and using a subsample of labor-intensive firms. Labor-intensive firms are defined as having a ratio of number of employees to sales larger than the quarterly median. ***, **, and * indicate two-tailed statistical significance at levels 1%, 5%, and 10%, respectively. N/A stands for “not applicable” when there is no improvement in RMSEs.

Table 5. Association between aggregate cost stickiness and future unemployment rate –
VAR model based on Barnichon and Nekarda (BN) (2012)

$$AZ_t = \phi Z_{t-k} + \varepsilon_t, \text{ where } Z_t = \left(ln\ s_{t,} ln\ f_{t,} \Delta\ ln\ u_{t,} ln\ uic_{t,} \Delta\ ln\ hwi_t, CostStickiness\right)'$$

Panel A: Impulse-responses graphs to shock in aggregate cost stickiness

Response: Unemployment rate



Panel B: Out-of-sample predictive performance

	Forecast horizon (quarters)				
Model	*t+0*	*t+1*	*t+2*	*t+3*	*t+4*
BN VAR without cost	0.130	0.301	0.559	0.874	1.078
BN VAR with cost stickiness	0.117***	0.268**	0.477**	0.786**	1.086
	(0.007)	(0.038)	(0.046)	(0.046)	N/A
BN VAR with cost stickiness, labor-intensive firms only	0.111**	0.247**	0.471***	0.777**	1.079
	(0.016)	(0.013)	(0.003)	(0.022)	N/A

Table reports the results of a VAR model (Barnichon and Nekarda 2012) that includes the following variables: inflow rate into unemployment (f_t), outflow rate out of unemployment (s_t), unemployment rate (UR_t), composite help-wanted index (HWI_t), initial unemployment insurance claims (UIC_t), and aggregate cost stickiness ($CostStickiness_t$). Panel A shows the impulse-response function (IRF) graph for the response of unemployment rate to a one-standard-deviation shock to *CostStickiness*. 95% confidence bands are also presented (shaded areas). Variables are defined in Appendix A. Panel B presents root-mean-squared-errors (RMSEs) between actual unemployment rate and the forecast values from the VAR model presented in Panel A using 10-year rolling windows, with and without the inclusion of cost stickiness. Clark and West (2007) *p*-values to compare the RMSEs across models excluding and including cost stickiness are shown in parentheses below the RMSE values. Two estimations of cost stickiness are shown: using the entire Compustat sample of firms, and using a subsample of labor-intensive firms. Labor-intensive firms are defined as having a ratio of number of employees to sales larger than the quarterly median. ***, **, and * indicate two-tailed statistical significance at levels 1%, 5%, and 10%, respectively. N/A stands for "not applicable" when there is no improvement in RMSEs.

Table 6. The predictive performance of combined forecasts with and without aggregate cost stickiness, compared to SPF forecasts

Panel A: Combined forecasts from models with no cost stickiness

	Forecast horizon (quarters)				
Model	*t+0*	*t+1*	*t+2*	*t+3*	*t+4*
SPF	0.134	0.295	0.489	0.703	0.920
Combined without cost stickiness	0.121***	0.283**	0.501	0.779	1.073
	(0.001)	(0.021)	N/A	N/A	N/A
Combined with cost stickiness	0.115***	0.281***	0.475***	0.751	1.002
	(0.001)	(0.003)	(0.005)	N/A	N/A
Combined with cost stickiness, labor-intensive firms only	0.107***	0.261***	0.482***	0.756	1.046
	(0.000)	(0.000)	(0.002)	N/A	N/A

Panel B: Combined forecasts from models with cost stickiness

	Forecast horizon (quarters)				
Model	*t+0*	*t+1*	*t+2*	*t+3*	*t+4*
Combined with cost stickiness	0.115	0.281	0.475	0.751	1.002
SPF	0.134***	0.314***	0.489***	0.703	0.920
	(0.001)	(0.003)	(0.005)	N/A	N/A
SPF, financial industry forecasters	0.133***	0.306***	0.471	0.677	0.890
	(0.001)	(0.008)	N/A	N/A	N/A
SPF, nonfinancial industry forecasters	0.142***	0.327***	0.515***	0.736	0.959
	(0.000)	(0.001)	(0.001)	N/A	N/A

Panel A compares root-mean-squared-errors (RMSEs) of unemployment forecasts from SPF panelists to the RMSEs of a combination of forecasts produced by statistical models, excluding and including cost stickiness. Cost stickiness is estimated in two ways: using the entire Compustat sample, and for labor-intensive firms only. Labor-intensive firms are defined as having a ratio of number of employees to sales larger than the quarterly median. Panel B compares RMSEs of a combination of forecasts produced by statistical models including cost stickiness to forecasts from SPF panelists according to their industry of employment. Clark and West (2007) *p*-values to compare RMSEs are shown in parentheses below the RMSE values. ***, **, and * indicate two-tailed statistical significance at levels 1%, 5%, and 10%, respectively. N/A stands for "not applicable" when there is no improvement in RMSEs.

Table 7. The predictive performance of aggregate cost stickiness in recessionary periods

Panel A: Interaction with indicator variables for start and end of recession

$$ChUR_{t+k} = \alpha_{1k} + \alpha_{2k}\, CostStickiness_t + \alpha_{3k}\, CostStickiness_t \times RecessionBegin_t + \alpha_{4k}\, CostStickiness_t \times RecessionEnd_t + \boldsymbol{\alpha}\, \mathbf{Controls_t} + \varepsilon_{t+k}$$

	Forecast horizon (quarters)				
	t+0	*t+1*	*t+2*	*t+3*	*t+4*
$Coststickiness_t$	–0.243***	–0.222***	–0.165**	–0.124**	–0.094*
	(–3.16)	(–2.86)	(–2.43)	(–1.99)	(–1.74)
$CostStickiness_t*RecessionBegin_t$	–0.077	0.079	–0.143	–0.465	–1.027*
	(–0.22)	(0.24)	(–0.35)	(–0.95)	(–1.89)
$CostStickiness_t*RecessionEnd_t$	–1.864***	–2.083***	–1.601***	–1.041*	–0.708
	(–2.83)	(–3.86)	(–3.03)	(–1.96)	(–1.38)
$AdvGDP_t$	–0.221***	–0.226***	–0.192***	–0.158***	–0.141***
	(–3.90)	(–3.94)	(–3.86)	(–3.38)	(–3.34)
Control variables	Yes	Yes	Yes	Yes	Yes
Number of quarters	115	115	115	115	115
Adjusted *R*-squared	0.610	0.664	0.637	0.594	0.591

Panel B: Excluding financial crisis period (Q4:2007 to Q1:2009)

	Forecast horizon (quarters)				
	t+0	*t+1*	*t+2*	*t+3*	*t+4*
CostStickiness	–0.227***	–0.200***	–0.136**	–0.092*	–0.063
	(–3.03)	(–2.82)	(–2.29)	(–1.78)	(–1.37)
$AdvGDP_t$	–0.136***	–0.128***	–0.095***	–0.062***	–0.055***
	(–2.79)	(–3.46)	(–3.75)	(–2.97)	(–2.65)
Control variables	Yes	Yes	Yes	Yes	Yes
Number of quarters	109	109	109	109	109
Adjusted *R*-squared	0.542	0.643	0.707	0.740	0.746

Panel A repeats the analysis in Panel A of Table 3 and evaluates the performance of *CostStickiness* at turning points in the business cycle: *RecessionBegin* and *RecessionEnd* are indicator variables for the starting and ending quarters of recessionary periods, respectively, as defined by the National Bureau of Economic Research. Panel B estimates the regression in Panel A of Table 3 with the financial crisis period excluded. Variables are defined in Appendix A. *t*-statistics shown in parentheses underneath the estimated coefficients are based on Newey and West (1987) heteroskedasticity and autocorrelation-consistent standard errors with three lags. ***, **, and * indicate two-tailed statistical significance at levels 1%, 5%, and 10%, respectively.

Table 8. Cross-sectional analyses

Panel A. Strength of governance mechanisms in place

$$ChUR_{t+k} = \alpha_{1k} + \alpha_{2k}\ \textit{Strong Govern. CostStickiness}_t + \alpha_{3k}\ \textit{Weak Govern. CostStickiness}_t + \boldsymbol{\alpha}\ \textbf{Controls}_{\mathbf{t}} + \varepsilon_{t+k}$$

	Forecast horizon (quarters)				
	t+0	*t+1*	*t+2*	*t+3*	*t+4*
Strong Govern. CostStickiness $_t$	–0.221**	–0.353***	–0.436***	–0.501***	–0.505***
	(–2.20)	(–4.59)	(–4.87)	(–5.09)	(–4.76)
Weak Govern. CostStickiness $_t$	–0.126	–0.086	–0.085	–0.076	0.013
	(–0.97)	(–0.97)	(–1.04)	(–1.07)	(0.22)
AdvGDP $_t$	–0.212***	–0.216***	–0.159***	–0.109**	–0.092**
	(–3.70)	(–4.15)	(–3.91)	(–2.60)	(–2.42)
Control variables	Yes	Yes	Yes	Yes	Yes
Number of quarters	70	70	70	70	70
Adjusted R-squared	0.703	0.817	0.831	0.831	0.822

Panel B. Asset intensity

$$ChUR_{t+k} = \alpha_{1k} + \alpha_{2k}\ \textit{Hi Asset-Intensity CostStickiness}_t + \alpha_{3k}\ \textit{Lo Asset-Intensity CostStickiness}_t + \boldsymbol{\alpha}\ \textbf{Controls}_{\mathbf{t}} + \varepsilon_{t+k}$$

	Forecast horizon (quarters)				
	t+0	*t+1*	*t+2*	*t+3*	*t+4*
Hi Asset-Intensity CostStickiness $_t$	–0.049	0.043	0.087	0.093	0.067
	(–0.58)	(0.55)	(1.13)	(1.21)	(0.95)
Lo Asset-Intensity CostStickiness $_t$	–0.13	–0.222**	–0.248**	–0.290**	–0.300**
	(–1.21)	(–2.30)	(–2.37)	(–2.50)	(–2.47)
AdvGDP $_t$	–0.270***	–0.281***	–0.237***	–0.190***	–0.169***
	(–3.77)	(–3.81)	(–4.04)	(–4.06)	(–4.62)
Control variables	Yes	Yes	Yes	Yes	Yes
Number of quarters	114	114	114	114	114
Adjusted R-squared	0.576	0.626	0.629	0.627	0.625

Panel C. Industry concentration

$$ChUR_{t+k} = \alpha_{1k} + \alpha_{2k}\, \textit{Lo Conc. CostStickiness}_t + \alpha_{3k}\, \textit{Hi Conc. CostStickiness}_t + \boldsymbol{\alpha}\, \textbf{\textit{Controls}}_t + \varepsilon_{t+k}$$

	Forecast horizon (quarters)				
	t+0	*t+1*	*t+2*	*t+3*	*t+4*
Lo Conc. CostStickiness$_t$	–0.028	–0.027	–0.029	–0.047	–0.063
	(–0.39)	(–0.37)	(–0.40)	(–0.70)	(–1.01)
Hi Conc. CostStickiness$_t$	–0.153*	–0.128*	–0.104*	–0.109*	–0.127**
	(–1.75)	(–1.88)	(–1.66)	(–1.84)	(–2.09)
AdvGDP$_t$	–0.262***	–0.272***	–0.229***	–0.181***	–0.159***
	(–3.68)	(–3.60)	(–3.73)	(–3.57)	(–3.90)
Control variables	Yes	Yes	Yes	Yes	Yes
Number of quarters	114	114	114	114	114
Adjusted *R*-squared	0.579	0.614	0.605	0.590	0.586

Table repeats the analysis in Panel A of Table 3 for versions of *CostStickiness* estimated in different subsamples. Panel A evaluates the predictive power of cost stickiness for firms with weak and strong governance mechanisms in place. *Strong* (*Weak*) *Govern. CostStickiness* is an estimation of cost stickiness for firm years in which *BCF Entrenchment Index* is higher (lower) than the quarterly median. Panel B evaluates the predictive power of cost stickiness for asset-intensive firms and firms that are not. *Hi (Lo)Asset-Intensity CostStickiness* denotes an estimation of cost stickiness for firm-quarters in which the ratio of total assets to sales is greater (less) than the quarterly median. Panel C evaluates the predictive power of cost stickiness for firms operating in concentrated vs. unconcentrated industries. *Hi (Lo) Conc. CostStickiness* is an estimation of cost stickiness for firm years in which *the Herfindahl-Hirschman Index* is higher (lower) than the quarterly median. Variables are defined in Appendix A. *t*-statistics shown in parentheses underneath the estimated coefficients are based on Newey and West (1987) heteroskedasticity and autocorrelation-consistent standard errors with three lags. ***, **, and * indicate two-tailed statistical significance at levels 1%, 5%, and 10%, respectively.

Table 9. The predictive performance of aggregate cost stickiness—using alternative measures of cost stickiness

Panel A: Cost Stickiness estimated based on Weiss (2010)

	Forecast horizon (quarters)				
	t+0	*t+1*	*t+2*	*t+3*	*t+4*
Weiss (2010) CostStickiness$_t$	–0.302***	–0.292***	–0.310***	–0.306***	–0.294***
	(–2.63)	(–3.03)	(–2.90)	(–2.76)	(–2.74)
AdvGDP$_t$	–0.224***	–0.236***	–0.189***	–0.142***	–0.122***
	(–3.03)	(–3.19)	(–3.25)	(–2.86)	(–2.93)
Control variables	Yes	Yes	Yes	Yes	Yes
Number of quarters	115	115	115	115	115
Adjusted *R*-squared	0.598	0.642	0.623	0.598	0.584

Panel B: Cost Stickiness estimated based on Balakrishnan, Labro and Soderstrom (2014)

	Forecast horizon (quarters)				
	t+0	*t+1*	*t+2*	*t+3*	*t+4*
BLS (2014) CostStickiness$_t$	–0.166	–0.179**	–0.160*	–0.172*	–0.195*
	(–1.47)	(–2.00)	(–1.88)	(–1.97)	(–1.97)
AdvGDP$_t$	–0.272***	–0.283***	–0.238***	–0.191***	–0.170***
	(–3.80)	(–3.71)	(–3.85)	(–3.74)	(–4.20)
Control variables	Yes	Yes	Yes	Yes	Yes
Number of quarters	115	115	115	115	115
Adjusted *R*-squared	0.583	0.625	0.617	0.604	0.601

Panel C: Cost Stickiness estimated based on Anderson, Banker, and Janakiraman (2003) with inventory changes

	Forecast horizon (quarters)				
	t+0	*t+1*	*t+2*	*t+3*	*t+4*
CostStickiness$_t$	-0.225***	-0.218***	-0.182**	-0.166**	-0.097
	(-3.07)	(-2.88)	(-2.31)	(-1.99)	(-0.97)
AdvGDP$_t$	-0.268***	-0.278***	-0.235***	-0.188***	-0.166***
	(-5.32)	(-6.65)	(-5.94)	(-4.96)	(-4.54)
Control variables	Yes	Yes	Yes	Yes	Yes
Number of quarters	115	115	115	115	115
Adjusted *R*-squared	0.574	0.621	0.621	0.614	0.608

Table repeats the analysis in Panel A of Table 3 for versions of *CostStickiness*, estimated using different methodologies. Variables are defined in Appendix A. *Weiss (2010) CostStickiness* in Panel A is an alternative measure of aggregate cost stickiness constructed by estimating a firm-level cost stickiness measure following Weiss (2010) and aggregating the firm-level measures into an aggregate cost-stickiness measure in each quarter. *BLS (2014) CostStickiness* in Panel B is an alternative measure of aggregate cost stickiness constructed following Balakrishnan, Labro, and Soderstrom (2014). In Panel C, we re-run the Anderson, Banker, and Janakiraman (2003) estimation procedure for *CostStickiness* but include changes in inventory in the dependent variable: $log\left[\frac{(COGS+\Delta INV+SG\&A)_{i,q}}{(COGS+\Delta INV+SG\&A)_{i,q-4}}\right]$, where $\Delta INVi,q$ is the change in inventory level observed in quarter q. All measures of aggregate cost stickiness are normalized by subtracting the sample mean and dividing by the standard deviation. *t*-statistics shown in parentheses underneath the estimated coefficients are based on Newey and West (1987) heteroskedasticity and autocorrelation-consistent standard errors with three lags. ***, **, and * indicate two-tailed statistical significance at levels 1%, 5%, and 10%, respectively.

Chapter 3. Global Oil Imbalance and the Cross-Section of Currency Returns

Abstract

Economists have long been puzzled by the natural causal relationship between oil balance of trade and countries' macroeconomic aggregates. In this study, we investigate the impact of crude oil balance of trade on the cross-section of currency returns on a sample of 36 countries, including both large oil exporters and importers. Using classical empirical asset pricing methodology, we find that a long-short portfolio of currencies sorted on oil balance of trade -the global oil imbalance factor- is priced after controlling for well-established financial factors such as carry, momentum, and value. The global oil imbalance factor induces an annual risk premium ranging from 2.4 to 2.9%. The risk premium is robust to various specifications and is found at both individual and portfolio levels. To the best of our knowledge, this is the first study that investigates the risk involved by the oil balance of trade in the cross-section of currencies. Hence, we contribute to a recent and actively growing body of literature trying to explain the cross-section of excess returns in that asset class (Lustig, Roussanov and Verdelhan 2011; Della Corte, Riddiough and Sarno 2016b; Colacito, Croce, Gavazzoni and Ready 2018). Finally, we compare the predictive power of oil balance of trade characteristic and its factor beta, and confirm that financial and macroeconomic characteristics subsume factor beta, which is consistent with the findings of BKRY (2018) in the currency market and Chordia, Goyal and Shanken (2015) in the equity market. In addition, we show that the net oil balance of trade characteristic, specific to each country and varying over time, contains incremental information relative to the carry characteristic that explains currency excess returns. The fact that not only oil price but also oil net balance of trade plays a role in asset pricing is completely new to the literature.

1. Introduction

Researchers and policymakers have long been captivated by the link between exchange rates and changes in oil prices. Three transmission channels of oil shocks to exchange rates have been identified: the terms of trade, wealth transfer, and portfolio reallocation. The first channel emphases the relative importance of tradable versus non-tradable sector of a country in its currency responses to oil shocks, and the last two channels focus on the effect of capital flows between oil importing and exporting nations on the determination of exchange rates (Barsky and Kilian 2004; Arezki *et al.* 2017). Given the level of oil imports and exports (oil balance of trade) in a country, oil price fluctuation significantly shifts wealth and induces capital flows between oil-importing and oil exporting nations. In a general equilibrium setting, oil price fluctuations also cause changes in countries' oil balance of trades. An increase (decrease) in oil price will lead to an increase of oil exports (imports) from exporting (importing) nations. Hence, the change in wealth in a country is a combined effect of changes in oil prices and changes in the country's oil imbalance of trade. While oil price shocks induce oil imbalance of trade, oil prices and oil imbalance of trade provide distinct information. Oil imbalance of trade categorizes a country as a net importer or exporter, which cannot be known by observing only changes in oil prices. A surge in oil price can increase or decrease wealth of a country depending on whether the country is a net importer or exporter. Exchange rate response to oil price shocks is structurally contingent on the sign of the oil balance of trade. Hence, this study is focused on the informativeness of oil (im)balance of trade in relation to exchange rates as well as currency excess returns.

Most previous studies investigate the effect of oil price shocks on exchange rates over time for individual countries, either importing or exporting nations. Empirical evidence is mixed (Beckmann and Czudaj 2013; Habib, Bützer and Stracca 2016, among others). Instead of studying the effect of price shocks in a time series fashion, we conduct our analysis cross-sectionally, comparing this effect among countries at each time period. This allows us to examine heterogeneous behaviors of exporters and importers at any point in time. To the best of our knowledge, this is first cross-sectional study relating the impact of oil balance of trade to currency excess-returns.

Our study is inspired by the recent work of Della Corte *et al.* (2016b).The authors find that external imbalances can explain the cross-section of currency excess returns and consider external imbalances as a risk factor. The authors argue that countries with high external imbalances are exposed to higher systematic risk and that investors holding their currency should be compensated by higher expected returns[32]. From a theoretical perspective, the relationship between countries' external imbalances and exchange rate movements is in line with exchange rate theory based on capital flows in imperfect capital markets. Kouri (1976) establishes a link between exchange rates and the balance of payments in an economy and shows that domestic current account surplus (deficit) is concomitant with an appreciation (depreciation) of the domestic currency. Gourinchas and Rey (2007) show that deteriorations in external accounts imply excess returns on the net foreign portfolio through the valuation channel or future trade surpluses through the trade channel. Adjustments to country's external accounts can serve as predictors of net portfolio returns and net export growth which, in turn, can be used to predict exchange rates in- and out-of-sample. A recent study by Gabaix and Maggiori (2015)

[32] On June 26th, 2013, *The Financial Times* credited the sharp 22% depreciation of the Indian rupee relative to the USD to investors' fear for India becoming one of the exposed emerging market currencies to its current account deficit.

illustrates why international imbalances are a fundamental driver of currency risk premium in their theoretical model of exchange rate determination: net debtor currencies are predicted to depreciate at times when risk-bearing capacity drops and to generate an excess return in equilibrium. As risk-bearing capacity grows, expected (required) excess returns will be greater. Hence, currency investors require a premium to hold the currency of debtor countries compared to creditor countries.

Consistent with these theoretical predictions, Della Corte *et al.* (2016b) show that sorting currencies on countries' external imbalances, proxied by net foreign assets and liabilities denominated in domestic currencies, generates a large spread in returns and find that a long/short global imbalance factor is priced in the cross-section of their currency sample using portfolios as test assets. Yet, recent development in the empirical asset pricing literature shows that tests performed using portfolios as test assets are not necessarily equivalent to tests performed with individual assets. Ang, Liu and Schwarz (2017) show that this effect is particularly severe when the number of assets is time-varying and limited in the cross-section. This is precisely the case in the currency market. The number of free-floating currencies is restricted and varies over time, which raises concerns about inference. In particular, the introduction of the euro currency induces a large heterogeneity in the number of currencies available to trade across periods. Barroso, Kho, Rouxelin and Yang (2018) (BKRY (2018) thereafter) tackle this issue and use individual currencies as test assets. The authors find limited evidence to support the relevance of the external imbalance once controlling for financial variables such as carry, momentum and value. This is puzzling and inconsistent with the theoretical models described previously, which engages us to be skeptical about the driving force of external imbalances that could be related to shocks in the global economy. While puzzling, the empirical disconnection between traditional macro factors and expected return has also been witnessed in the equity market and has attracted researchers' attention for decades.

In light of the mixed evidences described above, a commodity traded in the market, important input (net importers) or output (net exporters) of the economy such as crude oil may capture more dynamically important macroeconomic fluctuations that affect foreign exchange rates. Crude oil trade balance makes up a significant portion of countries' balance of trade, and hence, has a crucial impact on nations' current account. One might wonder whether there exists any relationship between oil balance of trade and countries' current account and if it depends on the sign of the oil bill. When oil bill is positive (negative), countries are considered as oil exporters (importers). Holding oil price constant, when oil exporting countries increase their oil trade balance, they shift more resources from the non-tradable sector to the tradable sector. Oil exporters behave as if this raise in oil trade balance is permanent and save the new found-wealth as suggested by the permanent income hypothesis. This newly gained income is saved instead of being spent in domestic matters. This inclination is reflected as an improvement of the current account. Empirically, Huntington (2015) reports a strong trend for current account balance to become more positive as net exporter's oil bill grows in these nations, supporting theoretical models. This tendency is more mitigated for oil import countries. High oil import bills are not systematically associated with a deterioration in the current account balance.

For the past 30 years, financial economists have believed that exchange rates are unpredictable and that the random walk model outperforms any economic model at least over the short-run (1 to 12 months) [33]. A recent body of the literature has shown interest

[33] See Meese and Rogoff (1983) puzzle and the excellent survey from Barbara Rossi (2013) about the disconnection between macro variables and exchange rates over time.

in explaining the cross-section of currency returns using macroeconomic variables. While time-series analyses for an investment strategy focus on a time-varying net long investment in risky assets, cross-sectional analyses of investment strategies are based on zero-net investment long/short portfolios. The time series strategy takes a directional position on an asset by only looking back at its own performance during the ranking period, and not based on its relative rank across a cross-section of different assets. A recent study from Goyal and Jegadeesh (2017) compares the performance of time-series and cross-sectional strategies across multiple international asset classes with heterogeneous return distribution and find that scaled cross-sectional strategies significantly outperform their scaled time-series counterparts. In light of these results, we decide to revisit the Meese and Rogoff (1983) exchange rate puzzle in a cross-sectional context and attempt to contribute to a literature recently resurrected.

More importantly, we decide to conduct this cross-sectional analysis using a variable related to oil, a traded commodity, instead of using a constructed macroeconomic variable such as external imbalances in Della Corte et al. (2016). Measurement errors in constructed macroeconomic variables represent a significant impediment on their ability to explain the currency excess returns. Measurement of macroeconomic variables involves a number of statistical and conceptual complexities. Most of these indicators are adjusted after their initial publication as they are difficult to measure in real time. Hence, we observe different historical vintage of constructed macroeconomic variables released several months after the date of the economic time period they represent. In addition, macroeconomic indicators are persistent and released at a low frequency relative to the frequency of market price updating. Another issue concerns the role of investors' expectations. If expectation of future macroeconomic indicator growth is entirely built into today's valuations, asset price movements will tend to precede developments in the underlying economy. Altogether, inherent limitations of constructed macroeconomic indicators represent a significant impediment to predict asset pricing returns and may explain the apparent disconnection between constructed macroeconomic variables and asset prices. It may explain why global external imbalance is unable to explain currency excess returns in certain asset pricing tests, in particular with individual currencies as test assets. In fact, Della Corte *et al.* (2016b) admit the limitation of the external liabilities denominated in domestic currency macroeconomic data they use:

"Clearly, accurately measuring the share of external liabilities in foreign currency is a hard task, in addition to the well-known difficulties in gathering data on derivatives positions."

In contrast, balance of trade is a measure of the physical movement of goods across borders commonly recorded by customs. The measurement of merchandise trade is well defined by international guidelines[34] and well-coordinated internationally[35]. The United Nations Statistical Division recommends to promote international comparability of merchandise trade data, and, for practical reasons, most countries provide value and quantity imports C.i.f. (i.e. including Cost, Insurance and Freight), and exports F.o.b. (free on board, i.e. excluding freight and insurance costs). International guidelines and its relative fungibility facilitate oil balance of trade measurements, significantly more reliable than constructed macroeconomic aggregates.

[34] United Nations, International Merchandise Trade Statistics: Concepts and Definitions, Studies in Methods Series M, No 52, Rev2, New York 1998. In 2000, the UN Statistics Division, with the help of an international expert group, produced a compiler's manual giving detailed advice on how to compile trade data.

[35] The "International Trade Statistics Task Force", comprising representatives from WTO, UN, OECD, IMF, WCO and Eurostat, is playing a major role in elucidating statistical problems and in harmonizing international practices.

Countries' oil balance of trade fluctuates over time depending upon positive and negative oil price shocks. At a given point in time, fluctuation in nations' oil balance of trade leads to appreciation or deterioration of their current account. While oil trade balance plays a major role in exchange rate determination through adjustments to the current account, we recognize that other financial and macroeconomic variables possibly capture these dynamics. Our study solely focuses on oil trade balance which, admittedly, is only one of the factor prone to predicting the cross-section of currency returns.

This paper provides insights about the currency risk premium induced by a risk factor constructed through a variable that captures both macroeconomic and market information: countries' oil balance of trade. We show that sorting currencies on their countries' net oil balance of trade generates a large spread in returns. In fact, a zero-cost high minus low risk factor that captures exposure to global oil imbalance explains a large variation of currency excess returns in a standard asset pricing model, using both individual currencies and portfolios as test assets. In addition, unlike external imbalances found in Della Corte *et al.* (2016b), oil imbalance characteristics provide incremental information to carry while external imbalance is totally subsumed by carry (BKRY, 2018). This can be in part explained by the fact that oil imbalance not only affects nations' current account but also reflects market demand and supply to oil and, in turn, oil prices. Hence, our oil variable plays two roles in conveying information: one is similar to external imbalances because both variables should theoretically influence currency returns through the argument of capital flows between countries, and the other is related to financial markets. As a highly liquid traded commodity, it conveys timely and more transparent information about investors' expectations of underlying economic conditions than low-frequency constructed macroeconomic variables.

Our study is also closely related to two recent studies: Ready, Ready, Roussanov and Ward (2017) and Colacito, Croce, Gavazzoni and Ready (forthcoming Journal of Finance, 2018). Ready et al. (2017) compare intensive exporting commodity countries who have high average interest rates with countries that export finished goods who have low average interest rates to explain carry trade returns in the currency market. In their general equilibrium model of international trade, commodity-currency exchange rates and risk premium increase with productivity differentials and trade frictions. Colacito *et al.* (2018) provide novel empirical evidence about cross-country heterogeneity in exposure to global long-run growth news. In particular, the authors find that heterogeneous exposure to global long-run output growth risk is a currency risk-factor capable to explain a large portion of the variation of currency returns.

The rest of the paper is organized as follow. We conduct a thorough literature review and theoretical motivation in section 2. Section 3 provides information about our data sample as well as a description of the variables constructed. Section 4 describes the empirical asset pricing framework employed and discuss the results and section 5 concludes.

2. Literature review and theoretical motivations

2.1. The impact of exchange rates on oil prices

The fundamental underlying assumption that underpins the theoretical framework relating exchange rate and oil price is the fact that oil price is denominated in USD.

The following equation holds based on the law of one price:

$$\ln\left(S_t\left(\frac{USD}{FOR}\right)\right) = \ln\left(\frac{P_{oil}(USD)}{P_{oil}(FOR)}\right),$$

$$\ln\left(P_{oil}(USD)\right) = \ln\left(S_t\left(\frac{USD}{FOR}\right)\right) - \ln\left(P_{oil}(FOR)\right),$$

where $\ln(.)$ is the natural logarithm, $S_t\left(\frac{USD}{FOR}\right)$ is the currency spot rate in US dollar per unit of foreign currency, $P_{oil}(USD)$ is the price of oil in US dollar and $P_{oil}(FOR)$ is the price of oil in foreign currency.

The fundamental assumption that oil price is denominated in USD, illustrated by the equation above, has important implications on the causal effect of oil price shocks. Oil price shocks (denominated in USD) have distinct effects on each country depending on the structure of its economy. Hence, these shocks will have a different impact on oil exporters and oil importers. This is reflected by the following demand and supply sides response to USD oil price shocks.

On the demand side, an appreciation (depreciation) of the USD relative to the foreign currency increases (decreases) the oil price denominated in the foreign currency, *ceteris paribus*. In turn, an increase (decrease) in oil price may induce a decrease (increase) in demand for oil for non-US countries (Blomberg and Harris 1995; Akram 2009). Importers may reduce their oil importing below their basic demand. However when demand for other tradable goods (requiring oil as an input of production) increase in the global market increases, the increase in oil price can be passed through, and domestic demand for oil can remain high, which results in an increase in oil importing rather than a decrease.

On the supply side, a US dollar appreciation, leading to a rise in the oil price, provokes a positive supply response if drilling activity and production capacity allow it (Coudert, Couharde and Mignon 2008). Yousefi and Wirjanto (2004) argue that oil-exporting countries'[36]supply response to exchange rate fluctuations depends on their price strategy and, hence, is not systematic. In the case of partial or full exchange rate pass-through, oil-exporters might also decide to cut oil supply as a response to a depreciation of the US dollar to hold the oil price in US dollars fixed (Fratzscher, Schneider and Van Robays 2014). This is important because it creates heterogeneous responses to the USD shocks across oil-exporters.

The change in oil importing and exporting due to fluctuations in the USD is captured in the oil imbalance. Because oil imbalance directly affects current account and change in current account also affect exchange rates (more discussion on this in section 2.2), USD oil shocks contribute to heterogeneous exchange-rate fluctuations across countries. Different economic structures imply different responses in terms of oil importing and exporting, which creates a spread in oil imbalance among countries. Therefore, change in oil imbalance of trade captures the heterogeneous response of the USD shocks on foreign currency value among countries and can be used to predict exchange rates.

[36] By and larger represented by the Organization of the Petroleum Exporting Countries (OPEC) members.

2.2. The impact of oil prices on exchange rates

Researchers have identified 3 direct transmission channels of oil price fluctuations (due to other shocks rather than the USD shocks, for example, supply and demand in oil markets or global economic growth) to exchange rates: the terms of trade channel, the wealth effect channel and the portfolio reallocation channel.

Amano and Van Norden (1998) introduce the terms of trade channel to link the price of oil to the price level which affects the real exchange rate. If a country's non-tradable sector is more energy (in particular oil) intensive that that of the tradable sector, the output price of the non-tradable sector will increase relative to the output price relative to the tradable sector. At the cross-section of countries' currency returns, this implies that the country with the most energy intensive non-tradable sector will experience a real price appreciation due to higher inflation relative to other countries (Chen and Chen 2007; Habib *et al.* 2016). If the price of tradable goods is no longer assumed to be fixed, then it also affects the nominal exchange rate. Nominal exchange and inflation rate are interconnected through the purchasing power parity (PPP). If the price of oil increases, we expect the currency of countries with large oil dependence in the tradable sector to depreciate in nominal terms due to higher inflation to respect the covered interest rate parity and the law of one price. Nominal exchange rate changes are contingent on the impact of price fluctuations of non-tradable and tradable goods. In addition to affecting exchange rates, oil price fluctuation also affects import and export as mentioned in the discussion above. However, change in oil imports and exports across countries is different than the discussion above because we do not know the underlying drivers of oil price fluctuation in this case: supply disruption or growth in demand rather than the USD shocks. Regardless, oil price fluctuation induces change in amount of oil import and export. As such, oil imbalance captures the effect of oil price on exchange rates.

Golub (1983) and Krugman (1983) introduced the concept of wealth and portfolio channel. Bénassy-Quéré, Mignon and Penot (2007) show that if oil price increases, oil-exporting countries experience a wealth transfer from oil-importing countries in USD terms. The wealth channel reflects the subsequent short-run effect. When oil prices rise, oil exporting countries experience an improvement in exports and the current account balance in domestic currency terms. Hence, Beckmann and Czudaj (2013) demonstrate that oil-exporting countries' currency appreciates in effective terms when oil prices increase. Conversely, when oil price increases, oil-importers' currency depreciates in effective terms. If oil-exporting countries reinvest their revenues in USD assets, the US dollar may also appreciate in the short-run because of the wealth effect. Oil imbalance does not change but current account balance evolves due to oil price fluctuations. Hence, our oil imbalance is silent on this channel.

The portfolio channel is the third direct transmission channel. Habib *et al.* (2016), Coudert *et al.* (2008) and Bénassy-Quéré *et al.* (2007) evaluate the medium and long-run impacts on the US dollar relative to oil-exporters' currency. It relies on two factors. The first factor is the dependence of the US on oil imports relative to the share of US exports to oil-producing countries. The second is oil exporters' relative preferences and portfolio allocation for US dollar assets.

The three direct transmission channels describe the association between exchange rate and oil price in various contexts. It emphasizes the prominence of the economic singularities to address the question of causal effect between oil price movements and exchange rate fluctuations. Hence, currency response to oil shocks will be different conditional on the importance of the tradable versus non-tradable sector of a country, the central bank reinvestment in USD asset policy, the interest rate policy to manage inflation, the current account, countries net foreign assets to cite only a few. More importantly, the direct transmission channel heavily depends on a nation's oil dependency.

Although our oil imbalance cannot capture the last two channels, it encompass the benefits for oil importers or exporters when oil prices increase or decrease and would indirectly affect current account balance.

Exchange rate response to oil price shocks is structurally contingent on the sign of the oil balance of trade. From this ex-ante intuitive theoretical starting point, we expect this study to yield distinct empirical asset pricing results for oil exporter and oil importers. Several time-series analyses investigate directly the impact of oil price shocks on currency exchange rate for oil importers and exporters. Habib *et al.* (2016) finds no consistent evidence that the exchange rates of oil importers depreciate against those of oil exporters using shocks to oil prices in a SVAR model. He proves there is no exclusive link between real effective exchange rates and oil price of oil-importers and oil-exporters. He argues that countries with high oil surplus may intervene in the exchange rate market to prevent upward pressures which may explain the apparent disconnection. Relying on a sample of 10 countries, Beckmann and Czudaj (2013) demonstrate the oil price shock effect differs between and within the group of oil-importers and oil-exporters. Nominal depreciation is identified for importing and exporting countries but nominal price increases against the USD is primarily observed for oil-exporting countries. Bodart, Candelon and Carpantier (2012) classify 68 countries as commodity exporting or importing economies and proves that commodity producing countries exhibit a robust relationship between increase in commodity prices and real exchange rate appreciations, conditional on the top exporting commodity making up at least 20% of aggregate exports. All these studies investigate time-series predictability of foreign exchange rate but do not explore cross-sectional predictability of currency returns. While time-series strategies take on a time-varying net long investment in risky assets, cross-sectional strategies are zero-net investment long-short strategies. Our paper investigates the latest. To the best of our knowledge, this is first cross-sectional study relating the impact of oil balance of trade to currency excess-returns.

2.3. Relationship between oil prices and current account

The relationship between oil price shocks and current account is well-documented in the economic literature. The impact of oil price shocks on the current account was first discussed by Agmon and Laffer (1978). Following the oil crises in 1973, they scrutinized wealth and income effects of this oil price shock on industrialized countries. They discover that balances of payment and the trade balances of high-income countries worsened noticeably after the oil price shock. Kilian, Rebucci and Spatafora (2009) confirm an increase in global imbalances driven by oil price shocks prior to financial markets and economic crises. Using time non-separable preferences, Schubert (2014) theoretically describes this deterioration and a slow improvement over time. Gao, Kim and Saba (2014) observe the adjustment load on oil or less energy-intensive goods respond more elastic to variations in income than energy-intensive goods. Relying on a general-equilibrium model, Backus and Crucini (2000) prove that oil accounts for a very large portion of the variation in the terms of trade over the last twenty-five years. Kilian *et al.* (2009) scrutinize the non-oil tradable goods that are crucial in determining the magnitude of the impact of oil price shocks on the current account. In building a two-country DSGE model, Bodenstein, Erceg and Guerrieri (2011) motivate these empirical results theoretically and add that the lack of empirical evidence during periods of time can be caused by the simultaneous existence of several shocks, along with diverse sources of oil price movements. Using a DSGE model, Leduc and Sill (2004) find that 40 percent of the adjustment to oil prices result from monetary policy, while Carlstrom and Fuerst (2006), using different assumptions, dispute such an impact. Kilian and Lewis (2011) also do not find evidence that monetary policy responses to oil price shocks have significant macroeconomic impact. Bodenstein, Guerrieri and Kilian (2012) emphasize the importance of the source of the oil price shock to define the optimal monetary policy response. Using an estimated GSGE model, Bodenstein *et al.* (2011) determine that non-oil trade is crucial for the transmission of shocks that affect oil prices.

Other time-series studies focus on the relationship between crude oil trade and nation's current account conditional the sign of their crude oil balance of trade: net oil importer or exporters. Dependence on oil trade have an incidence on a country's general trade deficit. Huntington (2015) probes the nature of this relationship and whether it holds equally to oil-exporting and oil-importing countries. They find that net oil exports are a significant factor in explaining current account surpluses but that net oil imports often do not impact current account deficits. The only exception they report applies to rich oil- importing countries where higher oil imports appear to contribute to greater current account deficits because these countries may view oil income gains and losses as temporary income sources that influence their saving patterns. As the economy contracts, both oil and non-oil imports decline. Exports may not drop as much unless the country trades significantly with other oil-importing nations. Exports may begin growing if they become cheaper through devaluation. The country may also attract foreign financial loans if interest rates rise relatively more than in other countries. Over the long run, the lending and borrowing practices of a country can be significant in defining how net exports respond to reduced oil import dependence. The trade balance may show a net decline after these adjustments if the country borrows from abroad. A deteriorating oil import bill may contribute to longer-run trends in current account balances if the private and public sectors in an oil-importing country viewed this income transfer as a temporary contraction in its income. Following Friedman (1957), the permanent-income hypothesis suggests that consumption will move with changes in permanent rather than total income. As total income declines, oil-importing nations may maintain their current aggregate consumption levels by reducing their domestic savings. As they become net borrowers to replace declining domestic savings, they maintain their consumption levels and continue to import more goods and services, causing a deterioration in their trade current account balances. Similar reasoning applies on oil-exporting countries if they view these income gains as temporary rather than permanent sources. As long as nations spend less of their temporary income than their permanent income, oil price movements could be a source of changes in net savings and hence current account imbalances (Barsky and Kilian (2004)).

Oil price shocks due to USD shocks, supply or demand shocks in oil market induces heterogeneous responses among oil importing and exporting countries. In turn, oil balance of trade fluctuations affect current account which have a direct connection to exchange rates. Dissimilar countries’ response to shocks at each point in time layout an ideal setting to study the cross-section of currency returns.

2.4. Cross-section of currency returns

As an alternative of studying the time-series relationship between oil trade and exchange rate like all investigations cited previously, our study focuses on the impact of oil trade on the cross-section currency excess return. We build on a growing body of research that explains the cross-section of currency excess returns using a range of investment strategies and conditioning characteristics: Lustig and Verdelhan (2007), Lustig *et al.* (2011) and Menkhoff, Sarno, Schmeling and Schrimpf (2012) investigate the carry strategy; Menkhoff *et al.* (2012) investigate momentum in the currency market, and value; Menkhoff, Sarno, Schmeling and Schrimpf (2016) implement a successful currency strategy using value. Asness, Moskowitz and Pedersen (2013) shows “Value and Momentum [is present] everywhere”, including in the currency market. Theoretical and empirical research in finance has tried to explain whether predictable excess returns generated by these strategies are compensated for systematic risk. Assuming investors’ risk aversion, classic finance theory states that returns in excess of the risk-free rate is a reward for exposure to one or multiple underpinning risk factors (Ross 1976). Specifically, a body of the literature finds evidence of a correlation risk (Mueller, Stathopoulos and Vedolin 2017), downside risk (Lettau, Maggiori and Weber 2014), global exchange rate risk (Lustig *et al.* 2011), and global unexpected volatility risk (Menkhoff *et al.* 2012). In spite of this, the literature has not be able to underpin macroeconomic roots conveying systematic risk. Currencies’ exposure to risk should, however, be driven by an underlying macroeconomic process. In the same way that in the equity market a firm’s level of risk is theoretically related to company fundamentals, a currency’s riskiness should be a function of the country’s underlying macroeconomic fundamentals. Verdelhan (2010) attempts to bridge this gap proposing that countries with high surplus consumption should compensate investors with higher currency returns relative to countries with low surplus consumption. Colacito and Croce (2013) and Farhi and Gabaix (2016) respectively prove that countries with high relative exposure to global consumption shocks and less resilience to large and rare economic shocks should reward investors with higher currency returns.

Others focus more specifically on macroeconomic variables to explain the cross-section of currency returns. Della Corte et al. (2016) investigate the relationship between countries' external imbalance and currency premium. They argue that countries with high external imbalance are exposed to higher systematic risk and that holding their currency should be compensated by higher expected returns. To support their claim, they create a long short external imbalance factor by double sorting on net foreign asset and liabilities denominated in domestic currency. Using portfolios of currencies as test assets, they find the external imbalance factor is priced at the cross-section of stock returns. BKRY (2018) revisit the relationship between countries' external imbalance and currency returns at individual currency level. Using individual test assets, they show that countries' external imbalance characteristics -net foreign asset and liabilities denominated in domestic currencies- have predicting power over the cross-section of currency returns but their effect is greatly subsumed by financial variables, in particular the carry trade characteristic. These finding are consistent with Koijen, Moskowitz, Pedersen and Vrugt (2018) who demonstrate that the carry characteristic predicts returns in the cross-section and in time-series across different asset classes including global equities, global bonds, commodities and currencies. They show that carry is not explained by known predictors of these asset classes. Yet, from a theoretical perspective, countries' external imbalance should have a significant influence in exchange rates movements. The spread in countries' external imbalances and their propensity to issue external liabilities in foreign currency must be related. However, as many macroeconomic indicators, net foreign assets and liabilities denominated in foreign currencies are updated at very low frequency and are subject to subsequent adjustments, or vintage variables. To reconcile economic theory that suggest that macroeconomic variables should explain currency returns and empirical findings showing that financial variables effectively explain financial returns, we choose to investigate the prominence of a variable closely linked to macroeconomic fundamentals as well as to the financial markets: oil trade balance. Interacted with the usual financial variables, studying the relationship between oil trade balance and currency returns would allow us to understand the role of each variables and their effect on currency returns.

2.5. Macroeconomic variables and asset pricing

While successful, the development of these theories has faced challenges to fully convince the academic community. In particular, the low frequency and relative inaccuracy of macroeconomic variables (since regularly revised after first publication) creates skepticism in respect to assessing their ability to explain the currency excess returns. Measurement of macroeconomic variables involves a number of statistical and conceptual complexities. These problems relate to the aggregation of heterogeneous microeconomic identities into a single macroeconomic figure. Aggregation of dissimilar microeconomic individual units into one macroeconomic aggregate variable may be incorrect and hazardous. For instance, GDP, unemployment, inflation statistics are often revised. When the UK economy went into recession in 2008, GDP statistics took several months to actually indicate the economy was in recession. Measuring accurately macroeconomic variables can be difficult because of problems with recording and collecting data. For example, the official balance of trade data for all the world's countries reports that exports exceed imports by nearly 1%. Therefore, it appears the world is running a positive balance of trade with itself, which cannot be true.

Moreover, macroeconomic indicators are persistent and released at a very low frequency relative to market price updating. Most of these indicators are readjusted after their initial publication as they are difficult to measure in real time. Hence, we observe different historical vintage of macroeconomic variables released several months after the date they are supposed to portray. Therefore, the low frequency update and real-time measure inaccuracy may affect their predicting power. Another issue concerns the role of investors' expectations. If expectation of future macroeconomic indicator growth is entirely built into today's valuations, asset price movements will tend to precede developments in the underlying economy. Altogether, inherent limitations of macroeconomic indicators explain their apparent inability to be useful predictors of asset returns in the empirical literature. Paradoxically, arbitrage pricing theory (Ross 1976) states that asset's expected returns should covary with macroeconomic variables, as a proxy for systematic risk. However, macroeconomic variables have largely failed to explain asset prices. Economic theory suggests that macroeconomic variables should explain currency returns. Empirical findings show that financial variables effectively explain large variations of currency returns. To reconcile economic theory and empirical findings, we choose to investigate the prominence of a variable closely linked to macroeconomic fundamentals as well as the financial markets: oil balance of trade. If the economy is growing quickly, it will likely consume more oil than it would if the economy were in a recession, as energy is an important input for economic growth. As such, oil price is closely tied to gross domestic product (GDP) and oil supply and demand, production and consumption give us an idea of the overall economic picture.

Moreover, crude oil futures come in as the third most liquid futures contracts[37] traded in the US market and ranks as the first among the commodity futures contracts with more than 800 thousands contracts traded on average per day in 2017. Furthermore, oil price is closely related to the overall state of the economy and it is traded in the financial markets incorporating new macroeconomic information on a daily basis. Hence, oil balance of trade appears to be a natural candidate to reconsider the lack of empirical relationship between macroeconomic variables and currency returns.

2.6. Oil Balance of trade to explain the cross-section of currency returns

First, the price of oil has a direct impact on countries' balance of trade. The balance of trade is the difference between the monetary value of a nation's exports and imports. Trade balance is the major component making up countries' current account and both terms are often used interchangeably. The current account is an important indicator about an economy's health. A positive current account balance indicates that the nation is a net lender to the rest of the world, while a negative current account balance indicates that it is a net borrower from the rest of the world. Naturally, with crude oil balance of trade being such a large component of many countries' balance of trade, oil price movements significantly shifts wealth between oil-importing and oil exporting nations. If two countries differ regarding the use of oil in production, increasing (decreasing) oil prices worsen (improve) the trade balance of non-intensive (intensive) oil exporters, leading to current account deficit (surpluses) and a deterioration (improvement) in the net-foreign asset position of these countries. Likewise, lower oil

[37] Top 5 traded future contracts, from highest to lowest volume: S&P 500 E-mini, 10-year T-notes, Crude oil, 5-year T-Notes, Gold.

prices increase corporate profitability and consumer spending which stimulates aggregate demand. Countries with higher oil balance of trade, which face higher demand, raise tradable production and shift more resources from the non-tradable sector to the tradable sector. This adds to the increase in current account imbalances. Current account adjusts through exchange rate corrections and real price. There is also a robust tendency of net oil exporters' current account to improve as oil price increase. Our study takes advantage of this strong and well-documented relationship between oil price and current account to investigate the impact of oil trade balance on the cross-section of currency excess returns.

Second, since oil is a commodity traded every day, the semi-strong form of the efficient market hypothesis (Fama 1965) states all publicly available information should be incorporated in oil pricing. Therefore, oil prices are likely to contain timely information about the global economy that macroeconomic indicators themselves such as GDP growth rates, inflation, and interest rates fail to reflect (Hamilton and Herrera 2004; Hamilton 2005). These macroeconomic variables are often seen as lagging indicators relative to asset prices.

Third, crude oil price has been found to comove with the aggregate stock market. Christoffersen and Pan (2017) shows that oil volatility has become a strong predictor of returns and volatility of the overall stock market after the financialization of commodity futures markets in 2004. They demonstrate that an increases in oil price uncertainty predicts tightening funding constraints of financial intermediaries, suggesting a link between the stock market and oil volatility risk. This effect is pervasive across asset classes. Oil prices have been found to covary with other asset markets including bond and commodities. Chiang, Ethan, Hughen and Sagi (2015) estimate the latent oil risk factors and establish their significance in pricing non-oil securities. They show that the average non-oil portfolio exhibits a sensitivity to the oil factors amounting to a sixth of that of the oil industry itself. Crude oil shocks have been found to have an impact on the U.S. bond market as well. Kang, Ratti and Yoon (2014) examine the effect of the demand and supply shocks driving the global crude oil market on aggregate U.S. bond index real returns. They find that a positive oil market-specific demand shock and positive innovation in aggregate demand is associated with significant decreases in aggregate bond index real returns for 8 and 24 months following the shock, respectively. More importantly, structural shocks driving the global oil market jointly account for 27.1% of the variation in real bond returns at 24 month horizon. This large figure reinforces the importance of oil price fluctuations in the bond market.

We focus on oil balance of trade rather than oil prices directly because it not only captures price fluctuations but also changes in oil production and consumption pattern. Higher oil export revenues increase the current account balance. Hence, the oil balance is expected to have a positive relationship with the current account. Moreover, crude oil is a very fungible commodity (despite differences in attributes such as density and gravity). Various price indices are strongly related and Brent measure has become a global leading price benchmark. Globalization and modern highly integrated economies guarantees a quasi-unique oil price worldwide that leads to a one-to-one mapping between oil balance of trade and the exchange rates.

The strong theoretical and empirical relationship between foreign exchange rate and current account, in addition to the well-documented impact of crude oil balance of trade on current account (which has been proven to be a risk factor in the currency market), makes crude oil balance of trade an ideal candidate to interact with the cross-section of currency excess returns. In the subsequent parts of the paper, we investigate the risk premium induced by countries' crude oil balance of trade on the cross-section of currency returns.

3. Data

This section describes all the data used in our study as well as the construction of the financial and macroeconomic variables of interest, the currency portfolios and the oil imbalance factor.

3.1. Main sample

The main data sample includes spot and 1-month forward rate, crude oil balance of trade and consumer price index for 36 countries, including large Economic Cooperation and Development (OECD) nations plus major players in crude oil production. To broaden the scope of the study and increase statistical power, we decide to include all countries available within the constraints of data available to us. We include the intersection of the countries available in the Enerdata dataset from the World Energy Statistics and the countries investigated by BKRY (2018), completed by currency return data available in Lustig *et al.* (2011). Countries are included in the sample if crude oil balance of trade, spot and forward rates are available. The sample comprises of the following countries: Argentina, Australia, Belgium, Brazil, Canada, Chile, China, Colombia, Czech Republic, Egypt, Euro, France, Germany, Indonesia, Italy, Japan, Korea, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Russia, Saudi Arabia, South Africa, Spain, Sweden, Taiwan, Thailand, Turkey, UA Emirates, Ukraine, United Kingdom. The Eurozone replace the countries that progressively joined the euro currency starting from January 1st, 1999. In their *2013 Triennial Central Bank survey of foreign exchange and derivative market activity*, The Bank for International Settlement reveals that the top 10 currencies account for 90 percent of the average daily turnover in foreign exchange markets. Our sample includes all currencies of the top 10 except the Swiss Franc because Enerdata does not provide crude oil balance of trade for Switzerland. In reality, our sample is more representative than this minimum threshold since it comprises 20 currencies within the top 25 currencies volume traded (the remaining missing crude oil balance of trade data). The number of currencies varies over time, reflecting several political economic changes observed during the length of our study. In particular, the number of currencies available shrinks over time due to the introduction of the Eurozone. Starting from January 1st 1999, Germany, Austria, Belgium, Spain, Finland, France, Ireland, Italy, Luxemburg, the Netherlands and Portugal gave up their respective currency to adopt the Euro as common currency[38]. After the introduction of the Euro, we remove the sequential new members of the Eurozone and replace the corresponding observations by a missing observation. In addition, a number of countries experience periods of political instability rendering inclusion of their currency unsuitable for the purpose of our study. Specifically, we exclude the Turkish Lira around the devaluation period from November 2000 to November 2001 and the Malaysian Ringgit during the period of capital control from May 1998 to June 2005. During the Turkish economic crisis in 2001, interest rate increased to levels of up to 3.00% monthly leading to failure in the covered interest rate parity. These periods of political instability are acknowledged in the foreign exchange literature and excluded for this reason (Lustig *et al.* 2011; Della Corte, Ramadorai and Sarno 2016a; Della Corte *et al.* 2016b, BKRY (2018)). Finally, we remove observations

[38] They are followed by Greece in January 1st 2001, Slovenia in January 1st 2007, Cyprus and Malta in January 1st 2008, Slovakia in January 1st 2009, Estonia on January 1st 2011, Latvia on January 1st 2014 and Lithuania on January 1st 2015 but these countries does not appear in our sample because we do not have their crude oil balance of trade.

when we detect large deviations from the uncovered interest parity condition. CIP deviations are likely to occur in period of distress in the foreign exchange market. These periods that can be particularly informative about the risk premium but most of these periods are characterized by extreme illiquidity and lack of tradability. Therefore, prices are basically uninformative.

Closing mid-point spot and forward rates are sourced from Thomson Reuters Datastream from August 31th, 1973 to August 31th, 2015. We start our empirical analysis in 1973 because it excludes periods of fixed exchange rates. Moreover, forward rate quotes are rarely available prior this date, preventing us from constructing the excess return variable. We follow the method prescribed by Bekaert and Hodrick (1993) to match carefully the forward rate to the appropriate spot rate using the standard date conventions. As in Fama (1984), we apply the natural logarithm to all spot and forward rates to be able to adapt our result to the direct or indirect quotation. The properties of the natural logarithm provides flexibility: going from direct to an indirect quote only entails a sing change but does not affect the absolute value. We use the indirect quotation. The spot and forward rates are presented in the form of U.S dollars per foreign currency. We carefully convert the base currency from Great British Pounds to United States Dollars when necessary, reflecting the global shift in base currency in the data. This transformation is necessary to include currencies still quoted in Great British Pound and form a more comprehensive data sample. We elect the monthly instead of daily exchange rate frequency because crude oil balance data are only updated at an annual frequency. Hence, we sample end of the month spot and forward rates to construct corresponding end of the month currency excess returns. Consumer price index data are source from the OECD’s Key Economic Indicators Database. Monthly CPI data is indexed to 100 in 2010.

The crude oil balance of trade data are sourced from the Global Energy Statistical Yearbook from Enerdata. Enerdata is an independent research and consulting firm specializing in the analysis and modelling of the global energy markets and its drivers. The dataset provides annual net crude oil balance of trade in millions of tons by country. This figure corresponds to difference between volumes of oil exported minus imported. Hence, a positive figure implies that the country of interest is a net exporter of crude oil in a given year. Conversely, a negative figure implies that the country of interest is a net importer of crude oil in a given year. Crude oil balance data are available at an annual frequency from 1990 to 2016. We construct monthly observations by keeping end of period data for oil trade balance constant until a new observation becomes available as in Della Corte *et al.* (2016b). Following the same literature, we extend the crude oil balance data backward to match the time series length of the spot and forward rate data[39]. The limited data availability for spot and forward exchange rates towards the beginning of the sample presents a potential degrees of freedom problem that we address by setting the minimum of 10 countries (following BKRY 2018). We do not include a time period that would not meet this minimum requirement in our results in our empirical tests.

3.2. Descriptive statistics

3.2.1. Crude oil balance of trade

The sample counts 12 net crude oil exporters and 24 net crude oil importers, for a total of 36 countries (Table 1). The mean of the crude oil balance of trade is negative (-17.6

[39] The relative stability of this measure in the empirical distribution suggests that this is a reasonable assumption. As a robustness test, we repeat the same analysis without backward extension, the main results remain virtually unchanged.

Mt) confirming that the majority of the countries in our sample are net oil importers. The monthly average volume of oil exported (78.446 Mt) is in the same order of magnitude than the volume of oil imported (71.866 Mt) which confirms the validity of our sample because oil imports should approximately equal to exports. An examination of the outliers shows that the Eurozone[40] is the largest crude oil importer with a time series balance of trade average of 538.62 million of tons imported per year. Kuwait, Russia, Saudi Arabia and UA Emirates are the largest crude oil exporter with a time series balance of trade average of 99.2, 215.8, 347.7 and 105.0 million of tons exported per year, respectively. Brazil is a net crude oil importer in the beginning of the sample and increase their annual average production of crude oil by 2.2 million of tons from 1990 to 2016 to become a net crude oil exporter in 2006. Conversely, the UK, China and Indonesia are net exporters at the beginning of the sample and become net importers starting from 2005, 1996 and 2009, respectively. Figure 1 – Panels A, B and C provides the evolution of net oil balance of trade for major oil exporters, importers and countries alternating net oil balance of trade sign, respectively.

3.2.2. Currency Excess Return

We define the natural logarithm of spot and forward exchange rates over the m-month period of currency i at the end of month t as $S_{i,t}$ and $F_{i,t}^{t+m}$, respectively. Exchange rates are expressed as the US dollars closing mid-price per unit of foreign currency such that an increase in $S_{i,t}$ indicates an appreciation of the foreign currency i relative to the US dollar. Currency excess return is defined as the return of the domestic investor (US

[40] We include the Eurozone in the sample to reflect the change to the Euro currency starting in January 1999. Eurozone is composed of the countries mentioned in section 3.1.

based) who borrows at the interest rate $i_{US,t}$ and invests the capital in a foreign currency $i_{i,t}$ at the end of period t:

$$RX_{i,t+m} = (S_{i,t+m} - S_{i,t}) + (i_{i,t} - i_{US,t}).$$

According to the covered interest parity condition, the forward premium equals the interest rate differential $F_{i,t}^{t+m} - S_{i,t} = i_{US,t} - i_{i,t}$, where $i_{i,t}$ and $i_{US,t}$ represent the natural logarithm of foreign and US risk-free rates, respectively, over the maturity of the forward contract. Akram, Rime and Sarno (2008) show that the covered interest parity condition holds closely in the data. Consequently, in natural logarithm terms, this is equivalent to the spot exchange rate return minus the forward premium:

$$RX_{i,t+m} = \left(S_{i,t+m} - S_{i,t}\right) - \left(F_{i,t}^{t+m} - S_{i,t}\right).$$

Simplifying the previous equation, the excess return on buying a foreign currency in the forward market at time t and then selling it in the spot market at time t + m is calculated as follow:

$$RX_{i,t+m} = S_{i,t+m} - F_{i,t}^{t+m}.$$

We construct 1-month ahead currency excess return as the difference between the spot rate at time t+1 and the time t forward rate with one month maturity. In the rest of the paper, we use the terms forward discount or interest rate differential relative to the US indifferently.

Table 1 also reports the mean and standard deviation of monthly currency excess returns (RX) and level oil balance of trade. On average, our sample of countries exhibits a positive monthly currency excess returns of 0.22% with a standard deviation of 2.99%. We also report the mean on standardized carry (0.037), 3-month momentum (0.042) and value (-0.026). The average currency excess return of oil exporter (0.348% per month) is more than twice as large as that of oil importers[41] (0.148%). The average excess return standard deviation of oil exporters is also lower (2.556% per month) relative to oil importers (3.245% per month). Oil exporters exhibit a mean on standardized carry (0.12), 3-month momentum (0.047), value (-0.042). Most exporters' currencies have performed relatively well over the sample considered. All monthly average excess returns are positive beside that of the UA Emirates which is slightly negative: -0.003%. A few oil importers display relatively large average monthly excess returns (above 0.3% per month): Brazil (0.965%), Egypt (0.823), Argentina (0.727%), Malaysia (0.475%), Kuwait (0.416%). 18 out of 23 oil importers show positive monthly average excess returns. A few oil importers display relatively large average monthly excess returns (above 0.3% per month): Turkey (0.850%), Indonesia (0.826), New Zealand (0.452%), Poland (0.361%). Portugal displays notable negative monthly average excess returns: -0.437%. These apparent large returns appear despite removal of observations failing the covered interest rate parity and periods of political instability described in Lustig *et al.* (2011). After closer examination of the data, we find no problem and thus include these observations.

3.3. Financial and macroeconomic variables (characteristics)

We follow the literature to construct the financial variables of carry, momentum and value (Lustig *et al.* 2011; Della Corte *et al.* 2016b). In addition, we construct a macroeconomic variable based on crude oil net balance of trade.

Carry characteristic: Carry trading is one of the most popular currency trading strategies. Investors buy high interest rate currencies and short low interest rate

[41] We calculate the equally weighted average excess returns of countries classified as oil importer or oil importer at time t.

currencies. The profitability of this strategy is driven by the uncovered interest rate parity puzzle. We use the interest rate differentials between a foreign country i and the domestic country (the US) to construct the carry characteristic:

$$Carry_{i,t} = i_{i,t} - i_{US,t}.$$

Under the assumption that covered interest rate parity holds[42], we can construct the carry characteristic equivalently using the forward discount rate in indirect quote:

$$FD_{i,t} = S_{i,t} - F_{i,t}^{t+m},$$

hence:

$$Carry_{i,t} = i_{i,t} - i_{US,t} = S_{i,t} - F_{i,t}^{t+m}.$$

We use the time t spot and 1-month maturity forward rate to construct the carry characteristic. This characteristic is standardized at the cross-section as described above.

Momentum characteristic: The momentum characteristic represents the persistence of short-term trends in the asset market. Momentum involves buying assets with high recent returns and selling assets with low recent returns. It has resulted in a very profitable investment strategy over time and across asset classes (Fama and French 1993; Jegadeesh and Titman 2001; Asness *et al.* 2013). For each currency i, we construct momentum using the change in the natural logarithm of the spot exchange rates over the last 3 months:

$$Mom_{i,t} = S_{i,t} - S_{i,t-3}.$$

[42] Taylor (1987) and Akram *et al.* (2008) confirms that the covered interest rate parity conditions hold empirically.

Value characteristic: Value is the relation between an asset's return and the ratio of its "long-run" value relative to its current market value. It captures the fact that spot exchange rate deviation from its long term value should revert toward equilibrium (equivalent to the book value of stocks, as described in Asness *et al.* (2013)). It is constructed using the change in real exchange rates over the last five year period:

$$Value = -\left(R_{i,t-12} - R_{i,t-60}\right)$$

$$= -\Big[\Big(S_{i,t-12} + \left(CPI_{i,t-12} - CPI_{US,t-12}\right)\Big) - \Big(S_{i,t-60} + \left(CPI_{i,t-60} - CPI_{US,t-60}\right)\Big)\Big],$$

where $R_{i,t-12}$ and $R_{i,t-60}$ are the real exchange rates USD per unit of foreign currency from 12 and 60 months prior to month t, respectively. The 12-months lagged starting point is the chosen to avoid an overlap with the momentum effect which is known to affect asset prices up to 12 months prior time t (Jegadeesh and Titman 1993). The real exchange rate is defined as $R_{i,t} = S_{i,t} + \left(CPI_{i,t} - CPI_{US,t}\right)$ where $CPI_{US,t}$ is the consumer price index for the United States at month t, and $CPI_{i,t}$ is the consumer price index for the foreign currency i at month t. Positive changes in real exchange rates correspond to a weaker US dollar relative to the foreign currency. Therefore, when a long-term negative change in real exchange rates is observed, we expect to see a positive coefficient for excess returns and currency appreciation.

Oil imbalance characteristic: We construct an oil imbalance characteristic based on annual crude oil balance of trade country data provided by Enerdata. A positive crude oil balance of trade implies that the country considered is a net oil exporter. Conversely, a negative crude oil balance of trade implies that the country considered is a net oil importer. We define the oil imbalance characteristic as the oil balance of trade:

$$Oil\ Imbalance_{i,t} = oil\ exporting_{i,t} - oil\ importing_{i,t}.$$

High (low or negative) oil imbalance of trade has a positive (negative) effect on current account which in turn affects positively (negatively) the related currency.

Financial and macroeconomic variables (characteristics) are all standardized in the cross-section. Using the information set available at time t, we calculate the cross-sectional mean and standard deviation of all currencies to operate the standardization as follow:

$$X_{s_{i,t}} = \frac{\left(X_{i,t} - \mu_{X_t}\right)}{\sigma_{X_t}},$$

where $X\_s_{i,t}$ is the standardized observation i at time t, $X_{i,t}$ is the characteristic i prior to standardization, and σ_{X_t} and μ_{X_t} represent the period t cross-sectional standard deviation and mean, respectively. The standardization expresses the variable $X\_s_{i,t}$ in standard deviations around the cross-sectional average. The cross-sectional mean is therefore 0 and is neutral to the base currency. Standardization presents several advantages. First, it mitigates the effect of outliers susceptible to drive empirical results. Second, it provides an intuitive interpretation of the results. When the independent variables of a regression increases by one standard deviation, the dependent variable increases by the estimated coefficient on the variable of interest. We define the predictive independent variables used in our study in the next subsections. The characteristics presented in this section are employed as predictors of the cross-section of currency excess returns when the empirical procedure uses individual currencies as test assets. They are also utilized to sort currencies in the cross-section to construct the financial and macroeconomic portfolios in the next section.

3.4. Financial and macroeconomic portfolios

The traditional empirical asset pricing procedure uses portfolios as test assets to identify risk premium. We create financial and macroeconomic quintile portfolios sorting on the corresponding standardized characteristics. These portfolios will be utilized as test assets in our empirical analysis. Following the construction of each financial and macroeconomic portfolio, we create the corresponding zero-cost, high minus low, risk factor (HML subsequently) buying the highest quintile portfolio (portfolio 5) and selling the lowest quintile portfolio (portfolio 1).

Currency carry portfolios: Based on the standardized carry characteristic, we construct five carry portfolios and use them as test assets in our empirical asset pricing investigation. At the end of each period t, we form five portfolios sorting on the standardized carry characteristic and allocating them from portfolio 1 to 5 based on their rank. As a clarification, we assign the 20% of all currencies with the highest forward discount (or highest interest rate differential relative to the US) to Portfolio 5 and the 20% of all currencies with the lowest forward discount (or lowest interest rate differential relative to the US) to Portfolio 1. The same logic applies to currency allocations in portfolio 2, 3 and 4. We rebalance these portfolios at each period t, hence currencies in each portfolio may be different over time. Following this dynamic asset allocation, we compute the 1-month ahead excess return for each portfolio as an equally weighted average of the currency excess returns within each portfolio. These 5 carry portfolios will be used as test assets in our empirical analysis. Finally, we construct a long/short zero-cost portfolio buying portfolio 5 and selling portfolio 1. We will use this portfolio as carry risk factor, denoted CAR, in our empirical analysis.

Currency momentum portfolios: At the end of each period t, we form five portfolios sorting on exchange rate returns over the previous 3 months, the standardized momentum characteristic. We assign the 20% of all currencies with the highest lagged exchange rate returns (winner currencies) to Portfolio 5 and the 20% of all currencies with the lowest lagged exchange rate returns (loser currencies) to Portfolio 1. Then, we compute the 1-month ahead excess return for each portfolio as an equally weighted average of the currency excess returns within that portfolio. Currency momentum portfolios are rebalanced each month. These 5 momentum portfolios will be used as test assets in our empirical analysis. Finally, we construct a long/short zero-cost portfolio buying portfolio 5 and selling portfolio 1. This portfolio will be used as momentum risk factor, denoted MOM3M, in our empirical analysis.

Currency value portfolios: At the end of each period t, we construct five portfolios sorted on the standardized value characteristic (Asness *et al.* 2013). We assign the 20% of all currencies with the lowest value characteristic to portfolio 1, and the 20% of all currencies with the highest value characteristic to portfolio 5. Then, we calculate the 1-month ahead the excess return for each portfolio as an equally weighted average of the currency excess returns within that portfolio. These 5 value portfolios will be used as test assets in our empirical analysis. Finally, we construct a long/short zero-cost portfolio buying portfolio 5 (undervalued currencies) and selling portfolio 1 (overvalued currencies). This portfolio will be used as value risk factor, denoted VAL, in our empirical analysis.

Currency oil imbalance portfolios: At the end of each period t, we construct five portfolios sorted on the standardized oil imbalance characteristic. We assign the 20% of all currencies with the lowest value characteristic to portfolio 1, and the 20% of all currencies with the highest value characteristic to portfolio 5. Then, we calculate the 1-

month ahead the excess return for each portfolio as an equally weighted average of the currency excess returns within that portfolio. These 5 oil imbalance portfolios will be used as test assets in our empirical analysis. Finally, we construct a long/short zero-cost portfolio buying portfolio 5 (relative exporters) and selling portfolio 1 (relative importers), denoted OIL. This portfolio will be tested as a risk factor in part of our empirical analysis. This construction is consistent with other financial and macroeconomic risk factors tested in the currency return literature. Della Corte *et al.* (2016b) construct similar quintile portfolios of external imbalance, Della Corte *et al.* (2016a) construct a volatility risk factor following the same approach. They then test the resulting zero-cost long/short portfolios as a global risk factor in the currency market.

3.5. Portfolio statistics

The oil imbalance portfolios: This section describes the excess-return properties of the oil imbalance sorted portfolios and the global oil imbalance factor. Table 2 – Panel A presents the 1 month average currency excess return of portfolio 1 to portfolio 5 as well as the returns of the zero-cost high minus low global oil imbalance portfolio (OIL). The average excess return increases monotonically from portfolio 1: -0.276% per annum to portfolio 4: 2.7% per annum. Portfolio 5: 1.668% per annum, is lower than portfolio 4 (2.7% per annum). We observe that annual volatility decreases from portfolio 2 to portfolio 5, with a significant drop in volatility in portfolio 5 relative to portfolio 4, which partially explains lower returns. Sharpe ratios also increase from portfolio 1 to 4, with a very slight decrease from portfolio 4 to 5 but remain very similar. When we compare the annual share ratios, we observe that long/short the oil imbalance portfolio has the highest Sharpe ratio (0.304) relative to other portfolios, apart from portfolio 4

(0.326). This comparison suggests that the oil imbalance portfolio has appealing risk-adjusted returns.

The financial portfolios: We also provide a comparison of the returns of the high minus low quintile portfolios based on the 3 financial characteristics in Table 2 panel B: carry, 3-month momentum and value, and the oil imbalance. The carry portfolio (CAR) shows very strong annual returns: 14.42%, more than 5 times higher than any of the 3 other strategies. At first, this result may appear surprising if we compare this figure to the average annual carry trade portfolio long/short spread. Della Corte *et al.* (2016b) report a spread of 4.67% per annum in their developed sample. However, Ready *et al.* (2017) develop a general equilibrium model of international trade and currency pricing in which they scrutinize commodity exporting highly dependent economies and focus particularly on oil exporting countries. They find that high-interest rate currencies tend to be commodity currencies, while low interest rate currencies tend to belong to countries that export finished goods and import large amount of commodities. They show that commodity country currencies are risky as it tends to depreciate in bad times, yet have higher interest rates on average due to lower precautionary demand, compared to the final-good producer. Our sample includes most of the major oil importers, which happen to be high interest rate currency countries as well as countries with large crude oil balance of trade. Not surprisingly, we observe that these currencies with high forward discount factors frequently fall in carry trade portfolio 5, which significantly increases the performance of the long leg of the carry trade portfolio (10.38% of average return per annum) relative to studies that focus exclusively on OECD or developed countries only (Della Corte *et al.* (2016b) report an annual average return of 5.31% for the same quintile portfolio in their developed sample). The carry trade short leg (portfolio 1) displays similar average return characteristics in our study compared to the literature.

Considering the extreme robustness of the carry portfolio returns in our data sample, its inclusion in any asset pricing tests is likely to subsume other strategies. Overcoming this significant impediment will be a sign of strong robustness of any other variable showing statistical significance. The annual standard variation of the financial portfolios (ranging from 9.35 to 10.084% per annum) is significantly larger than that of the oil imbalance portfolio (6.38% per annum). For instance, the carry trade portfolio has an annual volatility 58% larger than that of the oil imbalance portfolio.

Table 2 panel C shows the Pearson's correlation between these portfolios. Apart from a significant correlation between carry and oil imbalance portfolios (46%) which is consistent with explanation provided in the previous paragraph, we notice interesting properties from a portfolio diversification perspective of the latest which is negatively correlated with 3-month momentum (-14%) and shows low correlation with the value portfolio (16%).

4. Empirical Design

This section describes the asset pricing empirical methodology implemented to assess the information content of countries' net oil balance of trade. Following the literature (Lustig *et al.* 2011; Della Corte *et al.* 2016a; Della Corte *et al.* 2016b), we first assess the risk premium induced by the zero-cost high minus low global oil imbalance factor (OIL) at portfolio level using portfolios as test assets defined in section 3.4. Second, we address the same question using individual currencies as test assets as the two methodologies may not necessarily yield the same results (BKRY, (2018)). We control for financial characteristics defined in section 3.3. In each of these settings, we control for financial characteristics while using individual currencies as test assets or risk factors formed based on characteristics (section 3.5, while using portfolios as test assets) known to explain the cross-section of stock returns: carry, momentum and value.

4.1. Portfolio level empirical analysis

Della Corte *et al.* (2016b) show a zero-cost long/short external imbalance factor based on macroeconomic nations' characteristics (net foreign assets and liabilities denominated in domestic currencies) is priced at portfolio level. This implies that external imbalance is a proxy for systematic risk and commands a risk premium. As described in Section 2, oil balance of trade is directly connected to external imbalances and current account, which in turn influence foreign exchange rates. Consequently, we investigate the potential risk premium induced by the OIL factor in the cross-sectional variation in currency returns. In absence of arbitrage opportunities, the one-period ahead expected currencies excess return $\boldsymbol{RX_{i,t+1}}$ for country i discounted by the appropriate stochastic discount factor $\boldsymbol{M_{t+1}}$ is equal to zero. This is reflected by the following Euler equation:

$$\boldsymbol{E_t\left[M_{t+1}RX_{i,t+1}\right] = 0}.$$

We assume that the stochastic discount factor $\boldsymbol{M_{t+1}}$ is linear in pricing factors $\boldsymbol{f_{t+1}}$. It can be expressed as follow:

$$\boldsymbol{M_{t+1} = 1 - b^T(f_{t+1} - \mu)},$$

where $\boldsymbol{\mu}$ is the vector of factor means and $\boldsymbol{b^T}$ is the transposed vector of beta loadings. This linear model implies a beta pricing model. The expected returns is equal to the price of risk λ times the beta of each portfolio $\boldsymbol{\beta_f}$**:**

$$\boldsymbol{E}\left[\boldsymbol{RX}_{\boldsymbol{i},\boldsymbol{t}+\mathbf{1}}\right] = \boldsymbol{\lambda}^{\boldsymbol{T}}\boldsymbol{\beta}_{\boldsymbol{f}},$$

where the market price of risk can be calculated as:

$$\lambda = \mathrm{E}[(\boldsymbol{f}_{\boldsymbol{t}} - \boldsymbol{\mu})(\boldsymbol{f}_{\boldsymbol{t}} - \boldsymbol{\mu})^{\boldsymbol{T}}].\,\boldsymbol{b}.$$

$\mathrm{E}[(\boldsymbol{f}_{\boldsymbol{t}} - \boldsymbol{\mu})(\boldsymbol{f}_{\boldsymbol{t}} - \boldsymbol{\mu})^{\boldsymbol{T}}]$ is the variance-covariance matrix of the factor, and $\boldsymbol{\beta}_{\boldsymbol{f}}$ are the regression coefficients of the excess returns $\boldsymbol{RX}_{\boldsymbol{i},\boldsymbol{t}+\mathbf{1}}$ on the factors.

We estimate the portfolio price of risk λ using two different empirical asset pricing technique: the generalized method of moments (GMM) following Hansen (1982) and the two-stage Fama and MacBeth (1973) regression. We expect the results provided through the GMM and the two-stage Fama-Macbeth (1973) regression to be concomitant.

4.1.1. General Method of Moments (Hansen 1982)

The beta loadings $\boldsymbol{\beta}_{\boldsymbol{f}}$ are estimated via a time series ordinary least square (OLS) regressions of each test portfolio return on the set of pricing factors f and a constant:

$$\boldsymbol{RX}_{\boldsymbol{p},\boldsymbol{t}+\mathbf{1}} = \alpha_p + \sum_{f=1}^{F} \beta_{\boldsymbol{f},\boldsymbol{p}} x_{f,t} + \varepsilon_{p,t+1},$$

where $RX_{p,t+1}$ is the excess return of portfolio p at time t+1 and $x_{f,t}$ is the risk factor f at time t. α_p is the intercept, $\beta_{\boldsymbol{f},\boldsymbol{p}}$ is the beta loading of risk factor f and $\varepsilon_{p,t+1}$ is the t+1 residual all corresponding to the regression ran on portfolio p.

Our focus is on the OIL factor and we investigate whether this factor is priced. Previous studies find that other factors are also priced, in particular, CAR, MOM3M and VAL (Della Corte et al. (2016) among others) so we include them in our analysis. Different combination of these factors allow us to check the robustness of our OIL factor. We estimate $\boldsymbol{\beta_f}$ through 4 different OLS regressions, using the following set of risk factors from model (1) to model (4):

(1): OIL

(2): OIL and CAR

(3): OIL, CAR and MOM3M

(4): OIL, CAR, MOM3M and VAL

Once estimated, $\beta_{\boldsymbol{f,p}}$ are substituted in the beta pricing model:

$$\boldsymbol{E\left[RX_{p,t+1}\right] = \lambda^T \widehat{\beta_f}}.$$

The price of risk λ is estimated via the General Method of Moments (Hansen 1982). The objective is to test whether the beta pricing model can explain the expected cross-sectional returns of selected currency portfolios as asset test. In that respect, we only use the pricing errors as a set of moments, also called unconditional moments, and a pre-specified weighting matrix. We choose the first-stage GMM estimation using an identify matrix to price all the currency portfolios. In the first stage-GMM[43], the parameters are estimated based on the initial unity weight matrix, and no-updating of the weight matrix is performed. We elect an identity weight matrix because all moments should be treated with the same priority in term of information content in this empirical asset pricing exercise. Hence, we price all currency portfolios equally well. The tables

[43] As a robustness test, we attempt to price all the currency portfolios using a 2 stage GMM procedure. In the 2 stage GMM procedure, we specify the initial weight matrix to be identity to start the optimization problem. We obtain parameter estimates based in the identity matrix, compute new weight matrix based on those estimates, and then re-estimate the parameters based on that weight matrix. Results remain virtually unchanged. We only report the results based on the first-stage GMM procedure.

report estimates of the price of risk λ and statistical significance at the 10%, 5% and 1% level.

The results are presented in table 4. We estimate the price of risk λ using several set of risk factors and number of portfolios as test assets to insure the robustness of our OIL factor results. We first examine the OIL factor alone and an intercept and then include the CAR, MOM3M, VAL and an intercept[44] zero-cost high minus low risk factors depending on the specification. We run the 4 following factor pricing models:

$$E\left[RX_{t+1}^{p}\right] = \alpha^{p} + \lambda_{OIL}\beta_{OIL}^{p}, \quad (1)$$

$$E\left[RX_{t+1}^{p}\right] = \alpha^{p} + \lambda_{OIL}\beta_{OIL}^{p} + \lambda_{CAR}\beta_{CAR}^{p}, \quad (2)$$

$$E\left[RX_{t+1}^{p}\right] = \alpha^{p} + \lambda_{OIL}\beta_{OIL}^{p} + \lambda_{CAR}\beta_{CAR}^{p} + \lambda_{MOM}\beta_{MOM}^{p}, \quad (3)$$

$$E\left[RX_{t+1}^{p}\right] = \alpha^{p} + \lambda_{OIL}\beta_{OIL}^{p} + \lambda_{CAR}\beta_{CAR}^{p} + \lambda_{MOM}\beta_{MOM}^{p} + \lambda_{VAL}\beta_{VAL}^{p}, \quad (4)$$

where $E\left[RX_{t+1}^{p}\right]$ is the one-period ahead expected currencies excess return $\boldsymbol{RX_{i,t+1}}$ for country i, λ(k) is the expected market price of risk, with k=OIL, CAR, MOM3M or VAL, depending on the factor pricing model number, is estimated via GMM. First, for each currency, we run time-series regressions of portfolio excess returns against an intercept and the risk factors to estimate the price of risk of each risk factor $\lambda_{\boldsymbol{i}}$.

We estimate models (1) to (4) using different numbers of portfolios as test assets, respectively: 5, 10, 15 and 20 test portfolios. All test asset portfolios used here have been defined and described in the data section 3.4.2. Model (1) uses the 5 oil imbalance portfolio as test assets. Model (2) employs 10 portfolios as test assets: 5 oil imbalance

[44] According to Lustig *et al.* (2011) and Della Corte *et al.* (2016b), including an intercept is equivalent to including a zero-cost dollar risk factor, considered in the literature as one of the currency pricing kernels because it represents the expected market excess returns. DOL is an equally weighted strategy across the 5 carry quintile portfolios. The dollar risk factor has no-cross sectional relation with currency returns and it works as a constant that allows for mispricing.

and 5 carry trade portfolios. Model (3) utilizes 15 portfolios as test assets: 5 oil imbalance, 5 carry trade and 5 momentum portfolios. Model (4) uses 20 portfolios as asset tests: 5 oil imbalance, 5 carry trade, 5 momentum and 5 value portfolios.

We focus our attention on the sign and the statistical significance of the price of risk λ attached to the different risk factors, in particular the oil imbalance factor. A positive estimate on the global oil imbalance risk factor implies higher risk premium for currency portfolios whose returns positively comove with the global oil imbalance factor. Conversely, it implies a negative risk premium for currency portfolios exhibiting a negative covariance with the global oil imbalance factor. All price of risk λ estimates are annualized to ease interpretation. In model (1), the price of risk estimate on OIL is 2.3% (risk premium) per annum, economically and statistically significant near the 1% level. It means that currency excess returns positively comove with the global oil imbalance factor. In models (2)-(4), the risk premium on OIL is, respectively, 2.9%, 2.7% and 2.4% per annum and is statistically significant near the 1% level or beyond this threshold. The carry risk premium, strongly statistically significant and ranging from 14 to 14.4%. In models (3) and (4), similar comment applies for the momentum risk premium, statistically significant and ranging from 3.9 to 4.0%. In contrast, in model (4), VAL is not statistically significant. Across various specifications in terms of number of test assets and number of risk factors, currency excess returns always positively comove with the global oil imbalance factor. More importantly, we report a small range and robustness of global oil imbalance risk premium despite the diversity of test portfolios and control risk factors, overcoming, for example, the high hurdle imposed by the well-established dominant position of risk premium from carry factor.

4.1.2. Fama-MacBeth (1973) 2-stage procedure

Alternatively, we use the two-stage procedure of Fama and MacBeth (1973) to examine whether the OIL factor is priced. First, for each portfolio p, we run a time-series regression of the currency returns on a constant and the OIL factor alone, and a constant and the OIL factor interacting with the selected risk factors, CAR, MOM3M or VAL, to estimate the loadings of these factors $\boldsymbol{\beta_f}$. As in section 4.1.1, the loadings $\boldsymbol{\beta_f}$ are estimated through 4 time series OLS regressions of currency excess returns on the set of pricing factors over the entire time series of data as in models (1)-(4).

Then, prices of risk factors can be estimated as:

$$\boldsymbol{E\left[RX_{p,t+1}\right] = \lambda^T \widehat{\beta_f}}.$$

Specifically, we run T cross-sectional regressions (1 per period) of the excess returns $\boldsymbol{RX_{i,t+1}}$ on the estimated beta to estimate the T set of λ. Finally, we calculate the price of risk λ taking the time-series average of the coefficient estimated in the T cross-sectional regressions and the corresponding t-statistics.

The results are presented in table 5. As in table 4, we estimate the price of risk λ using several set of risk factors and number of portfolios as test assets to insure the robustness of our OIL factor results. We elect the same 4 factor pricing models as well as test portfolios presented in section 4.1.1 to be able to compare and assess the robustness of our results using a different asset pricing technique. We keep the same model indexing (1)-(4) for simplicity.

As in table 4, we focus our attention on the sign and the statistical significance of the price of risk λ attached to the different risk factors, in particular the oil imbalance factor, with similar interpretation of the results. All price of risk λ estimates are annualized. In models (1)-(4), the risk premium on OIL is, respectively, 2.9%, 2.9%, 2.7% and 2.4% per annum and is statistically significant near the 1% level or beyond this threshold in all specifications. The carry risk premium remain strongly statistically significant and positive, ranging from 14 to 14.4%. In models (3) and (4), similar comment applies for the momentum risk premium, statistically significant and positive ranging from 3.9 to 4.3%. VAL is again non-statistically significant. The R-squared is lower in model (1): 25.4% than that of other specifications, suggesting that there may be an important omitted variable in the regression. Indeed, when we add the carry risk factor, the R-squared increases significantly, as expected. OIL risk factor is statistically significant and capable to explain 25.4% of the cross-section variance of the return as a standalone variable as well as statistically significant in all other models. It shows that even if global oil imbalance is related to interest rate differentials, independent information in global oil imbalance matters in cross-section of currency returns.

The results estimated via the Fama and MacBeth (1973) 2-step procedure and General Method of Moments are extremely close, both in estimate and statistical significance of OIL and the other control risk factors. They both lead to the same conclusion: OIL is priced at the cross-section of currency returns, which suggests that oil imbalance is a global risk factor in the currency market.

4.2. Individual currency level analysis

The empirical asset pricing literature has been implementing two distinct approaches to determine if a factor is priced. The two methods differ in the type of test asset elected: individual assets or portfolios formed based fundamental variables that drive asset returns as test assets. Lewellen (2015) and Novy-Marx and Velikov (2015), among others, use individual assets as asset tests to estimate the cross-sectional risk premium, whereas many other studies following Fama and MacBeth (1973) use portfolios as test assets. Each approach has advantages and inconveniences. On one hand, grouping stocks into portfolios arguably reduces noise. On the other hand, Ang *et al.* (2017) show that aggregating stocks into portfolios has important pitfalls. It shrinks the cross-sectional dispersion of the betas, causing estimates of factor risk premium to be less efficient. This effect appears to be most prominent when there is a small and time-varying number of assets in the cross-section (Kan (2004) and (Ang *et al.* 2017)). This development is relevant to the currency market because of the limited number of tradable currencies. Therefore, in this section, we use individual currencies as test assets and the Fama and MacBeth (1973) procedure to examine the statistical significance of the price of OIL risk factor.

4.2.1. Global risk factor on individual currencies as test assets

Following similar empirical asset pricing methodology as section 4.2, we examine whether the OIL factor is priced at the individual currency level. We use the same factors constructed in section 4.2 as independent variables, but replace the portfolio returns in the left side of equations given in section 4.2 by individual currency returns as dependent variables. Specifically, we run a time-series regression for each currency to estimate loadings of individual currency return to the risk factors considered:

$$\boldsymbol{RX_{i,t+1}} = \alpha_i + \sum_{f=1}^{F} \beta_{i,f} x_{f,t} + \varepsilon_{i,t+1},$$

where $\boldsymbol{RX_{i,t+1}}$ is the period t+1 excess-return for currency i and $x_{f,t}$ is the high minus low risk factor f at time t. α_i is the intercept, $\beta_{i,f}$ is the loading on factor f and $\varepsilon_{i,t+1}$ is the t+1 residual corresponding to the regression ran on currency i. Once estimated via OLS regression, $\beta_{\boldsymbol{i,f}}$ are substituted in the pricing model:

$$E[RX_{i,t+1}] = \lambda^T \widehat{\beta_f},$$

where λ is price of risk. Then, we run T cross-sectional regressions (1 per period) of the excess returns $RX_{i,t+1}$ on the estimated betas to estimate T sets of λ. Finally, we calculate the price of risk λ taking the time-series average of the coefficient estimated in the T cross-sectional regressions. A positive estimate of the factor price of global oil imbalance risk implies higher risk premium for individual currencies whose returns positively comove with the global oil imbalance factor, and negative risk premium for currencies exhibiting a negative covariance with the global oil imbalance factor.

Table 6 report the estimates of the price of risk λ and statistical significance at the 10%, 5% and 1% level. In columns (1) to (3), we examine the global oil imbalance risk factor jointly with the common risk factors: carry, momentum and value. The coefficient on OIL is positive and statistically significant at the 10% level with coefficients ranging from 0.171 to 0.184. VAL is negative and statistically insignificant in all 3 specifications. MOM3M changes sign between specification (2) and (3) and is statistically insignificant. CAR is positive but statistically insignificant, surprisingly. Not only OIL is the only priced factor, but its homogeneous range of estimates of OIL across specifications is a sign of robustness. Demonstrating that OIL is not only priced at portfolio level, but also at individual asset level, provides further evidence that the global oil imbalance factor is a proxy for systematic risk in the currency market.

4.2.2. Role of characteristics in explaining the cross-section of currency excess returns

The results from the above section suggest that the loadings on financial factors, in particular, carry and our OIL factor commands a risk premium. In this section, we provide empirical evidence on the role of financial and oil characteristics in explaining the cross section of currency excess returns. We use the Fama and MacBeth (1973) procedure to regress currency excess returns on the oil imbalance interacted with the financial characteristics, carry, 3-month momentum, and value. At each time period t, we run a cross-sectional regression as follows:

$$RX_{i,t+1} = \alpha_t + \sum_{l}^{k} \gamma_{l,t} x_{l,i,t} + \varepsilon_{t+1},$$

where α_t represents the intercept at month t and ε_{t+1} represents the residuals at months t+1. $\gamma_{l,t}$ represents the coefficient of the lth independent variable $x_{l,j,t}$ at month t including financial and macroeconomic variables discussed above. Columns (1) to (3) in table 6 examine financial characteristics carry, momentum and value as unique independent variables of the regression. We observe that each of them exhibit a positive sign and is statistically significant at the 10% level at least. The carry characteristic is very large, ranging from 0.508 to 0.745% per month, and statistically significant far beyond the 1% level. A positive coefficient on carry implies that taking a long position in currencies with higher interest rates relative to the cross-sectional average predicts positive returns in the following period. Our results are consistent with the finding in the literature. Individually, momentum and value are positive statistically significant at the 1% level. Column (4) in table 6 report the results for oil characteristic interacted with all financial characteristics together. The coefficient on momentum and value is positive as expected but not statistically significant due to the presence of the carry strategy that subsume the other financial characteristics. As characteristics are standardized in the cross-section, a one standard deviation increase in carry predicts a monthly excess return of 70 basis points monthly (8.44% annually). The column (5) presents the interaction of the same 3 financial variables and the oil imbalance characteristic. Despite the prominence of the carry characteristic, oil imbalance characteristic is statistically significant at the 10% level. This constitute an additional evidence that oil imbalance characteristic plays a role in explaining currency excess returns.

4.2.3. Oil trade imbalance decomposition

The large performance of carry characteristic combined with its positive correlation with the oil imbalance characteristic raises potential concerns of about the incremental informativeness of the oil imbalance characteristic relative to carry. In table 7, we project the oil imbalance characteristic on carry to decompose the variable of interest into 2 components: a projection on carry and an orthogonal component - the residuals - uncorrelated with carry by construction. Each period t, we run the following cross-sectional regression:

$$Oil\ Imbalance_{i,t} = \beta_0 + \beta_1 \times Carry_{i,t} + \varepsilon_{i,t},$$

where $Carry_{i,t}$ is the carry trade characteristic in month t for country i, $Oil\ Imblance_{i,t}$ is net crude oil balance of trade for country i in month and $\varepsilon_{i,t}$ is the country i residual at time t. We then construct the projections of oil imbalance on carry and save their respective residual vector:

$$Proj\_oil\_car_{i,t} = \hat{\beta}_0 + \hat{\beta}_1 \times Carry_{i,t},$$

$$Res\_oil\_car_{i,t} = Oil\ Imbalance_{i,t} - Proj\_oil\_car_{i,t},$$

where $Proj\_oil\_car_{i,t}$ is the currency i projection of oil imbalance characteristic on carry characteristic at time t and $Res\_oil\_car_{i,t}$ is the orthogonal component of the currency i projection of oil imbalance characteristic on carry at time t.

We will use both projection and residual components in our empirical analysis. Both components are standardized following the procedure described in section 3.3. Finally, we substitute the projected and residual components to the oil imbalance characteristic in the Fama and MacBeth (1973) procedure to regress currency excess returns on the projections and residuals. At each time period t, we run a cross-sectional regression as follows:

$$RX_{i,t+1} = \alpha_t + \sum_{l}^{k} \gamma_{l,t} x_{l,i,t} + \varepsilon_{t+1},$$

where α_t represent the intercept at month t and ε_{t+1} represents the residuals at months $t+1$. $\gamma_{l,t}$ represents the coefficient of the lth independent variable $x_{l,j,t}$ at month t including financial and macroeconomic variables discussed above. The coefficients on the oil imbalance projection and on the orthogonal component (residuals) are the coefficients of interest. The coefficient on the oil imbalance projection on carry provides evidence about the informativeness of carry on the cross-sectional excess returns of currencies. The coefficient on the orthogonal component provides evidence about the incremental information contained by the oil imbalance characteristic but not contained in carry to explain the cross-section of currency excess returns. Considering the strength of the carry variable, we expect the projection of oil imbalance on carry to be a powerful predictor of currency excess returns. If the orthogonal component of the projection of oil imbalance on carry brings incremental information, it should help explain the cross-section of currency excess returns as well.

We test extensively the informativeness of the projected and orthogonal components of oil imbalance on carry in 8 different specifications of the Fama and MacBeth (1973) regressions controlling not only for financial characteristics but also for their corresponding beta loadings. Results are reported in table 7. As expected, the oil imbalance projection on carry *“proj_oil_car”* contains valuable information, economically and statistically significant at 1% level, to explain the cross-section of currency excess returns in all specifications (columns (5)-(8)). More importantly, we find that the orthogonal component contains incremental information relative to carry that helps to explain the cross-section of currency returns at 10% level at least in 7 out of 8 specifications. The unique specification that is below this threshold shows a t-statistic of 1.53 slightly below the 10% level. Moreover, specification column (8) that controls for all financial characteristics and their corresponding beta loadings is statistically significant beyond 1% level and is economically significant relative to other estimates (0.15 relative to -0.07 for momentum, for instance). Despite the excessive strength of the carry trade strategy, this extensive battery of tests guarantee that oil trade imbalance is a highly relevant characteristic to explain the cross-section of excess currency returns.

4.2.4. Beta versus characteristics: Fama-Macbeth (1973) approach

There is a growing body of literature about the predicting power of characteristics versus beta in the equity market (Fama and French (1993), Kent *et al.* (1997), Davis *et al.* (2000), Ang *et al.* (2017), Chardie *et al.* (2015) and BKRY (2018)) are the first to investigate the relative importance of characteristics versus betas in the currency market. They examine both financial and macroeconomic characteristics and beta loadings. They conclude that characteristics subsume beta loadings in the currency market for carry, momentum, value as well as the 2 macroeconomic variables making up external imbalance. Considering the limited theoretical evidence on the topic, results cannot be generalized. In this section, we examine the explanatory power of the oil imbalance characteristic and beta loading in our sample, as well as other financial variables. Using the Fama and MacBeth (1973) framework, we regress the individual cross-section of currency excess returns on the beta loading and characteristics.

We use the beta loadings estimated in section 4.2.1 and substitute them in the beta pricing model in addition to financial and macroeconomic characteristics:

$$\boldsymbol{E}\left[\boldsymbol{RX}_{\boldsymbol{i},\boldsymbol{t}+\boldsymbol{1}}\right] = \boldsymbol{\lambda}^{\boldsymbol{T}}(\widehat{\boldsymbol{\beta}_{\boldsymbol{f}}} + \boldsymbol{X\_s}),$$

where $\boldsymbol{X\_s}$ are the standardized financial and macroeconomic characteristics.

In table 7 column (1) to (6), we include the 4 characteristics defined in section 3.4.1 as independent variable and interact them with beta loadings of OIL, CAR, MOM3M and VAL. We find that characteristics dominate betas in all specifications. In fact, the carry characteristic subsume other characteristics as well. Oil imbalance characteristic is statistically insignificant and its sign switches across specifications. We notice that the carry characteristic exhibit a very large positive coefficient and statistical significance that is likely to subsume other potential predictors.

Despite the extreme strength of the carry characteristic, we attempt to assess the role of the oil imbalance characteristic as the only characteristic interacted with all beta loadings: OIL, CAR, MOM3M and VAL in column (8). We find that the coefficient on oil imbalance characteristic is positive, economically and statistically significant whereas all beta loadings are statistically insignificant. This is consistent with the evidence found in the equity market (Chordia *et al.* 2015) and in the currency market BKRY (2018) who find that relative to betas, firm characteristics consistently explain a much larger proportion of variation in returns in the equity market.

4.2.5. Beta versus characteristics: Double sorted portfolios

Fama and French (2008) observe that few extreme individual asset returns can potentially drive results in the Fama and MacBeth (1973) procedure. Double-sorted portfolios appear to be a reliable alternative used in the literature to confirm the Fama-MacBeth (1973) results. Hence, we examine the explanatory power of the loadings on the risk factors and characteristics using double-sorted portfolios on characteristics and beta. This exercise is often performed in the context of equity in the empirical asset pricing literature (Fama and French 1992; Lewellen 2015). Each period t, we first sort the currency sample on oil imbalance characteristic to split it in halves and then we sort the 2 subsamples based on beta loadings to split them in halves. Hence, we construct 4 currency portfolios of currency excess returns. Oil characteristic is defined in section 3.4.1 and beta loadings are the same as those estimated in section 4.2.2. Evidence in section 4.1 and 4.2 suggests that excess returns covary positively with the oil characteristic and beta, therefore we expect excess returns to be higher (lower) in the high (low) characteristic and beta groups relative to their respective low (high) groups.

Results are reported in table 8. The portfolios {characteristic, beta}: {high, high}, {low, high} and {high, low} are all statistically significant at 10% level at least. The characteristic-beta {high-high} group exhibits the highest excess return and is statistically significant at 1% level whereas the characteristic-beta {low-low} group has the lowest excess return and is statistically insignificant. The 2 characteristic-beta groups: {high, low} and {low, high} exhibit similar excess returns and statistical significance. We find that the 4 resulting characteristics-beta spreads are positive. In particular, conditional on low characteristic, the beta spread is large (0.193% per month) and statistically significant and conditional on low beta, the characteristic (0.188% per month) display similar attributes. We also notice that the 2 remaining spreads are statistically insignificant. This table allows us to refine the conclusions drawn about the relative importance of oil imbalance characteristics and beta loadings. As discussed in section 4.2.2 and documented in the literature, characteristics subsume beta when all observations are pooled together. However, conditional on low beta loading, oil imbalance characteristic contains valuable information to predict currency excess return, which is consistent with the literature. More importantly, we observe that conditional on low oil imbalance characteristic, beta loadings also carry valuable information to predict currency excess return, which was not the case when considering the entire pooled sample. Hence, we refine the inference drawn in section 4.2.2 and conclude that not only characteristics but also conditional beta loadings may bring incremental predictive information.

5. Conclusion

The recent empirical literature has attempted to shed the light on the macroeconomic forces driving currency risk premium. Sometimes controversial, the macroeconomic determinants underlying currency premium remain only partially understood. This paper tries to fill this gap and provide insights about the currency risk premium induced by a risk factor constructed via a variable that captures both macroeconomic and market information: countries' oil balance of trade. We show that sorting currencies on their countries' net oil balance of trade generates a large spread in returns. In fact, a zero-cost high minus low risk factor that captures exposure to global oil imbalance explains a large variation of currency excess returns in a standard asset pricing model, using both individual currencies and portfolios as test assets. The economic intuition for this risk factor is simply that net oil exporters offer a currency risk premium to compensate investors willing to hold an asset strongly correlated with supply, demand and price fluctuations of the oil market. This is understandable considering that many economies, especially large oil exporters, revolve almost entirely around oil exports. Their currency is inevitably exposed to macroeconomic shocks impacting their oil balance of trade. This systematic risk exposure naturally commands a return premium that we observe in our asset pricing tests. Overall, we provide empirical support for the existence of a meaningful link between macroeconomic fluctuations through the oil trade channel and exchange rate returns, revealing a fundamental source of risk driving currency returns.

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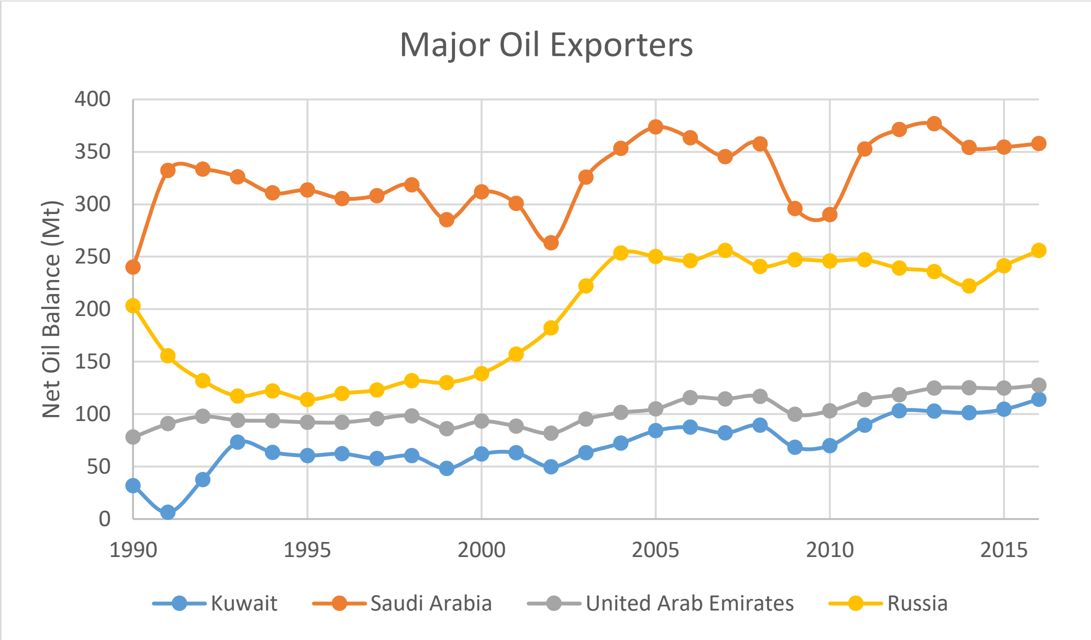
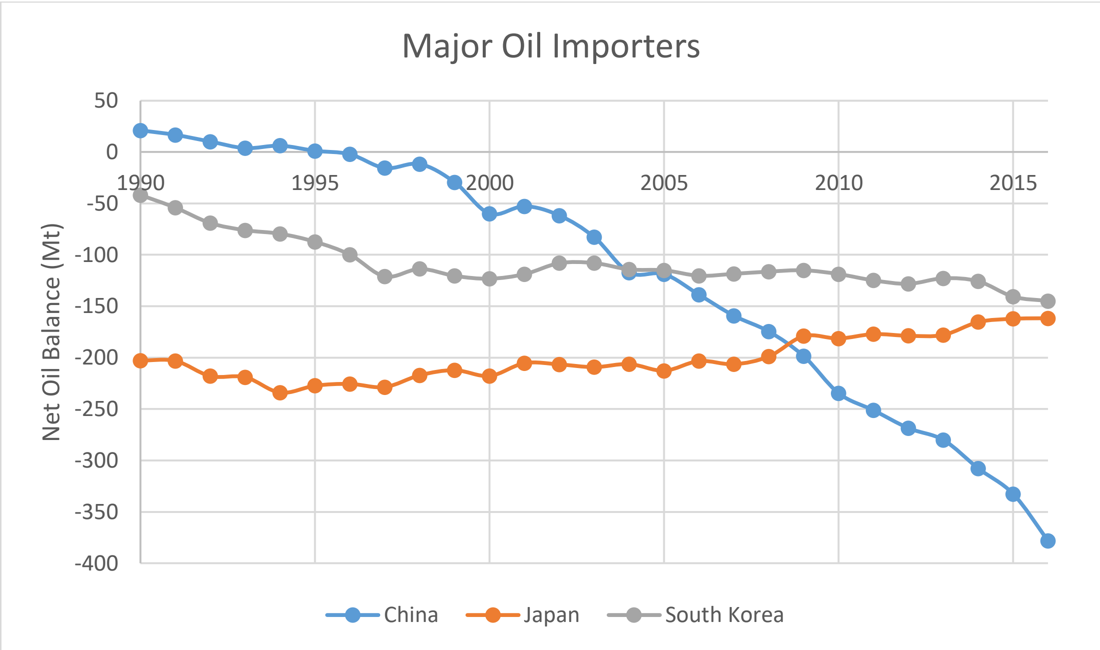
Figure 1: Oil importing and exporting trend

Figure 1 Panel A, B and C plot the evolution of crude oil net balance of trade over time for a few major oil exporters, oil importers and countries that change the sign of their oil net balance of trade during the sample considered.

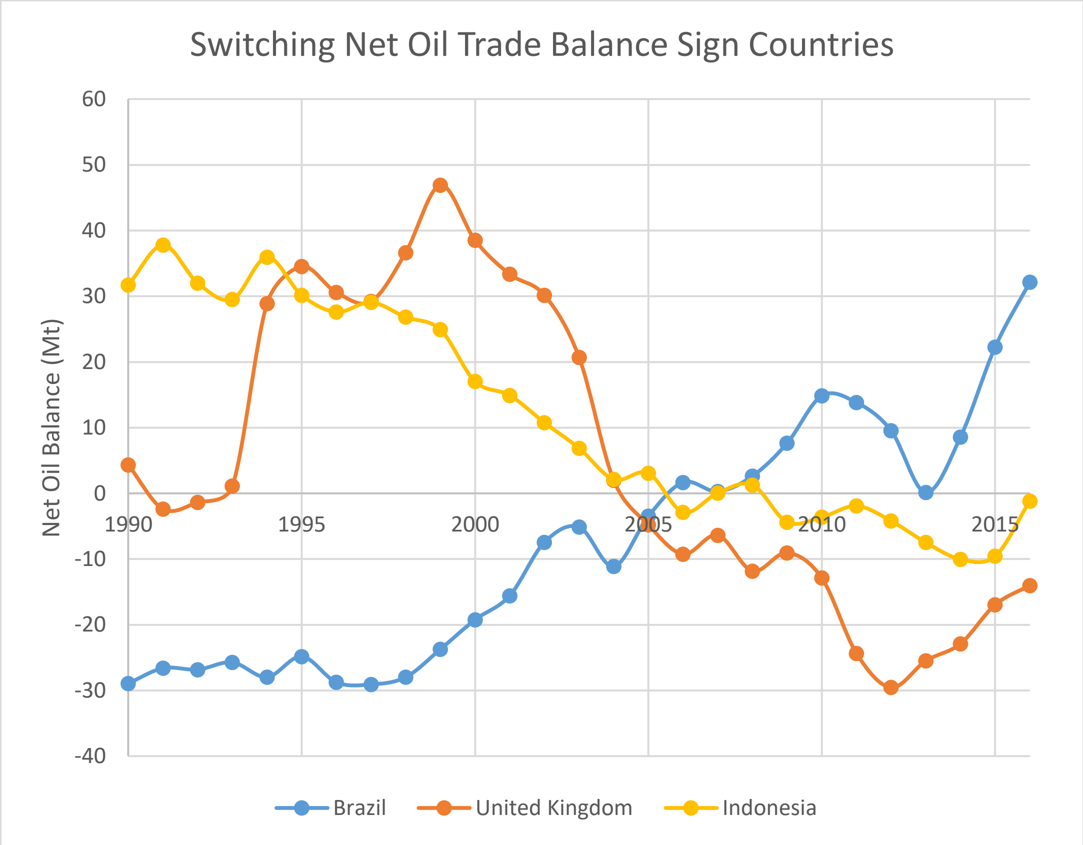
Panel A



Panel B



Panel C



Switching Net Oil Trade Balance Sign Countries
Net Oil Balance (Mt)
60
50
40
30
20
10
0
-10
-20
-30
-40
1990
1995
2000
2005
2010
2015
Brazil
United Kingdom
Indonesia

Table 1: Summary Statistics

This table shows the average and standard deviation of currency excess returns (RX), financial variables of carry (car), 3-month momentum (mom3m), 5-year value (val), and crude oil net balance of trade (oil) all of which are standardized in the cross section. We also include the non-standardized crude oil net balance of trade (lev_oil). The sample covers the period from August 1973 to August 2015 at a monthly frequency for all variables except for crude net oil balance of trade which is available at an annual frequency, and expressed as millions of tons (Mt). All exchange rates are quoted in terms of U.S. Dollars per unit of foreign currency. Averages given in the last row of the table represents the importer, exporter and overall average of the corresponding variables across all countries. Note that N/A indicates unavailable data either because excess returns are not available for at least 5 years or because CPI is missing, preventing us from construction value.

	RX		Car		mom3m		val		lev_oil		oil	
Country	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
Argentina	0.73	2.60	0.91	1.22	-0.53	0.96	N/A	N/A	3.48	2.19	0.08	0.01
Australia	0.23	3.49	0.07	0.77	0.10	0.87	-0.04	0.68	-6.71	2.68	0.04	0.05
Belgium	0.14	3.37	-0.31	0.52	0.17	0.56	0.16	0.82	-27.98	2.29	-0.08	0.04
Brazil	0.97	4.08	0.29	0.38	0.20	1.43	-0.91	1.68	6.94	6.88	0.10	0.05
Canada	0.01	2.00	-0.23	0.40	0.15	0.66	0.09	0.88	32.41	26.34	0.34	0.13
Chile	0.11	3.60	-0.09	0.31	0.05	0.98	-0.05	0.40	-9.77	0.81	-0.01	0.01
China	0.10	0.53	-0.33	0.41	0.15	0.66	N/A	N/A	-193.02	80.43	-1.24	0.52
Colombia	0.15	3.92	-0.03	0.36	0.16	1.19	N/A	N/A	21.81	9.62	0.20	0.07
Czech Republic	0.15	3.70	-0.19	0.35	0.13	0.96	-0.24	0.90	-6.90	0.71	0.01	0.03
Egypt	0.82	1.24	0.52	0.72	-0.10	0.76	N/A	N/A	3.69	3.20	0.08	0.03
Euro	-0.12	2.96	-0.28	0.36	0.07	0.70	0.03	0.50	-538.62	25.89	-3.68	0.19
France	0.09	3.21	-0.11	0.53	0.10	0.53	0.06	0.48	-77.15	3.82	-0.49	0.06
Germany	-0.00	3.36	-0.91	0.47	0.23	0.55	0.07	0.57	-92.19	6.48	-0.61	0.08
Indonesia	0.83	3.83	0.46	1.45	-0.11	0.89	N/A	N/A	-3.51	4.22	0.03	0.02
Italy	0.22	3.12	0.72	0.65	0.01	0.62	-0.10	0.60	-84.28	1.89	-0.55	0.05
Japan	-0.13	3.36	-0.89	0.63	0.10	1.02	-0.11	0.97	-203.26	15.87	-1.46	0.22
Korea	0.17	3.37	-0.18	0.30	0.12	0.77	0.06	0.85	-119.38	7.60	-0.75	0.04
Kuwait	0.42	2.32	0.11	1.29	0.24	0.68	N/A	N/A	99.19	6.83	0.71	0.04
Malaysia	0.48	1.90	0.05	1.35	0.34	0.70	N/A	N/A	2.39	1.59	0.07	0.01
Mexico	0.28	2.90	0.16	0.41	-0.00	0.84	0.19	0.84	82.90	15.16	0.64	0.12
Netherlands	0.03	3.36	-0.77	0.40	0.21	0.58	0.14	0.61	-51.05	4.98	-0.27	0.06
New Zealand	0.45	3.63	0.23	0.89	0.14	0.92	-0.15	0.76	-3.02	0.66	0.07	0.04
Norway	0.10	3.11	-0.04	0.51	0.11	0.62	0.06	0.41	92.79	29.99	0.82	0.21
Poland	0.36	3.89	0.14	0.58	0.11	1.03	-0.11	0.63	-19.98	3.22	-0.08	0.04
Portugal	-0.44	2.62	-0.36	0.17	0.13	0.61	0.23	0.02	-13.70	0.22	0.03	0.00
Russia	0.23	3.25	0.16	2.31	-0.17	1.02	-0.80	0.82	215.80	44.40	1.52	0.25
Saudi Arabia	0.27	2.81	-0.01	0.46	-0.02	0.99	1.05	0.84	347.66	28.42	2.37	0.13
South Africa	0.02	4.38	0.61	0.84	-0.21	1.14	N/A	N/A	-16.80	3.62	-0.04	0.05
Spain	0.26	3.24	0.88	0.82	0.05	0.67	-0.31	0.81	-54.00	1.73	-0.30	0.04
Sweden	0.01	3.18	-0.00	0.47	0.07	0.66	0.17	0.50	-18.24	1.37	-0.03	0.05
Taiwan	-0.01	2.59	-0.08	2.09	0.05	0.94	N/A	N/A	-45.37	5.64	-0.26	0.04
Thailand	0.06	3.29	-0.11	0.41	0.06	1.01	N/A	N/A	-37.37	4.21	-0.20	0.03
Turkey	0.85	3.90	1.11	1.24	-0.51	1.34	-0.15	0.68	-21.30	3.10	-0.09	0.03
UA Emirates	-0.00	0.09	-0.26	0.32	0.09	0.59	0.00	1.07	105.03	13.24	0.78	0.08
Ukraine	0.03	2.66	0.17	2.21	-0.32	1.14	N/A	N/A	-9.32	6.54	-0.01	0.06
United Kingdom	0.09	3.00	-0.07	0.43	0.14	0.72	-0.01	0.82	5.71	18.60	0.16	0.15
Oil Importer	0.15	3.25	-0.01	0.73	0.04	0.83	-0.02	0.63	-71.87	8.17	-0.43	0.08
Oil Exporter	0.35	2.56	0.12	0.78	0.05	0.86	-0.04	0.92	78.45	15.88	0.61	0.10
Average	0.22	3.00	0.04	0.75	0.04	0.84	-0.03	0.73	-17.59	10.96	-0.06	0.09

Table 2: Portfolio Statistics

Panel A: Oil imbalance portfolios

		Annual			Monthly	
OIL Portfolio	Obs	μ	σ	Sharpe Ratio	Skewness	Kurtosis
P1	475	-0.28	8.78	-0.03	-0.056	4.323
P2	475	1.63	9.99	0.16	-0.558	4.308
P3	475	2.68	9.58	0.28	-0.322	4.275
P4	475	2.70	8.28	0.33	-0.410	5.271
P5	475	1.67	5.93	0.28	-0.254	5.083
OIL	475	1.94	6.38	0.30	-0.269	4.841

Panel B: High minus low risk factors

		Annual			Monthly	
HML P5-P1	Obs	μ	σ	Sharpe Ratio	Skewness	Kurtosis
CAR	475	14.42	10.08	1.43	-0.715	5.163
MOM3M	475	3.64	9.48	0.38	0.319	4.844
VAL	443	2.77	9.35	0.30	0.083	4.605
OIL	475	1.94	6.38	0.30	-0.269	4.841

Panel C: Pairwise Pearson's Correlation

	CAR	MOM3M	VAL	OIL
CAR	1			
MOM3M	-0.17***	1		
VAL	0.080	-0.025	1	
OIL	0.46***	-0.14**	0.16**	1

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Panel A and B presents the descriptive statistics of the portfolio currency excess returns portfolios sorted on the time t. Panel A sorts assets on oil balance of trade. The first portfolio (P1) contains the top 20% of all currencies with low oil balance of trade whereas the last portfolio (P5) contains the top 20% of all currencies with high oil balance of trade. OIL is a long-short portfolio that buys P5 and sells P1. The table also reports the annualized standard deviation and Sharpe ratio as well as the monthly skewness and kurtosis. Panel B compares excess return statistics of long-short portfolios carry (CAR), 3-month momentum (MOM3M) and value (VAL). Panel C reports the Peason's pairwise correlation between the long-short portfolios the global oil imbalance factor (OIL), carry (CAR), momentum (MOM3M) and value (VAL). Excess returns are expressed in percentage per annum. The portfolios are rebalanced monthly, and the sample runs from August 1973 to August 2015. *t*-statistics are reported in parentheses.

Table 3: Currency Portfolios as test assets using the General Method of Moments (GMM)

Test Portfolios	Factor Loadings	Obs	Price of Risk	Z-statistics
5 P-Test: {OIL}	Cons	443	0.025***	(2.775)
5 P-Test: {OIL}	OIL	443	0.023**	(2.304)
10 P-Test: {OIL CAR}	Cons	443	0.021**	(2.385)
10 P-Test: {OIL CAR}	OIL	443	0.029***	(2.806)
10 P-Test: {OIL CAR}	CAR	443	0.144***	(8.739)
15 P-Test: {OIL CAR MOM3M}	Cons	443	0.024***	(2.699)
15 P-Test: {OIL CAR MOM3M}	OIL	443	0.027***	(2.594)
15 P-Test: {OIL CAR MOM3M}	CAR	443	0.144***	(8.748)
15 P-Test: {OIL CAR MOM3M}	MOM3M	443	0.040**	(2.534)
20 P-Test: {OIL CAR MOM3M VAL}	Cons	443	0.026***	(3.041)
20 P-Test: {OIL CAR MOM3M VAL}	OIL	443	0.024**	(2.330)
20 P-Test: {OIL CAR MOM3M VAL}	CAR	443	0.140***	(8.498)
20 P-Test: {OIL CAR MOM3M VAL}	MOM3M	443	0.039**	(2.502)
20 P-Test: {OIL CAR MOM3M VAL}	VAL	443	0.020	(1.279)

The table presents asset pricing results for currency strategies sorted on time t -1 information. Row numbered 1 to 5 include, respectively, 5, 10, 15 and 20 asset tests depending on the number of risk factors considered. Row 1 includes 5 oil imbalance strategies; row 2 includes 5 oil imbalance and 5 carry strategies; row 3 includes 5 oil imbalance, 5 carry strategies and 5 momentum strategies; row 4 includes 5 oil imbalance, 5 carry strategies, 5 momentum and 5 value strategies for a total of 4 strategies and 20 portfolios. The pricing factor carry (CAR) is the strategy that is long the 20% of forward discounts currencies and is short 20% of lowest forward discount currencies, both relative to the US. The pricing factor Momentum (MOM3M) is the portfolio that is long the top 20% currencies with the highest 3 month-returns (winner currencies) and is short the bottom 20% currencies with the lowest 3 month-returns (looser currencies). The pricing factor value (VAL) is the portfolio that is long the top 20% currencies with the highest five-year change in the natural logarithm of the real exchange rate (undervalued currencies) and is short the bottom 20% currencies with the lowest five-year change in the natural logarithm of the real exchange rate (overvalued currencies). OIL is the strategy that is long the top 20% of highest oil trade balance and is short the bottom 20% of lowest oil trade balance. We report first-stage GMM estimates market price of risk and the z-statistics in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Results rely on our main sample consisting of the 36 countries to construct the 20 asset tests and the 4 pricing factors. It runs from October 1978 to August 2015. Portfolios are rebalanced monthly.

Table 4: Currency Portfolios as test assets using Fama-MacBeth (1973)

	Monthly Currency Excess Returns			
	(1)	(2)	(3)	(4)
HML Beta Loadings	5 P-Test: {OIL}	10 P-Test: {OIL CAR}	15 P-Test: {OIL CAR MOM3M}	20 P-Test: {OIL CAR MOM3M VAL}
OIL	0.029**	0.029***	0.027**	0.024**
	(2.558)	(2.629)	(2.440)	(2.198)
CAR		0.142***	0.144***	0.140***
		(8.289)	(8.346)	(8.114)
MOM3M			0.042***	0.039**
			(2.611)	(2.450)
VAL				0.020
				(1.235)
Constant	0.027**	0.022*	0.025**	0.026**
	(2.387)	(1.894)	(2.224)	(2.322)
Obs	2,215	4,430	6,645	8,860
R-squared	0.254	0.410	0.427	0.427
N. of months	443	443	443	443

The table presents asset pricing results for currency strategies sorted on time t -1 information. Column 1 to 5 include, respectively, 5, 10, 15 and 20 test portfolios depending on the number of risk factors considered. Column 1 includes 5 oil imbalance strategies, column 2 includes 5 oil imbalance and 5 carry strategies, column 3 includes 5 oil imbalance, 5 carry strategies and 5 momentum strategies, column 4 includes 5 oil imbalance, 5 carry strategies, 5 momentum and 5 value strategies for a total of 4 strategies and 20 portfolios. The pricing factor carry (CAR) is the strategy that is long the 20% of forward discounts currencies and is short 20% of lowest forward discount currencies, both relative to the US. The pricing factor Momentum (MOM3m) is the zero-cost portfolio that is long the top 20% currencies with the highest 3 month-returns (winner currencies) and is short the bottom 20% currencies with the lowest 3 month-returns (looser currencies). The pricing factor value (VAL) is the zero-cost portfolio that is long the top 20% currencies with the highest five-year change in the natural logarithm of the real exchange rate (undervalued currencies) and is short the bottom 20% currencies with the lowest five-year change in the natural logarithm of the real exchange rate (overvalued currencies). OIL is the strategy that is long the top 20% of highest oil trade balance and is short the bottom 20% of lowest oil trade balance. We report Fama-MacBeth (1973) estimates market price of risk and the t-statistics in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Results rely on our main sample consisting of the 36 countries to construct the 20 test assets and the 4 pricing factors. It runs from October 1978 to August 2015. The portfolios are rebalanced monthly.

Table 5: Individual currencies as test assets on risk factors using Fama-MacBeth (1973)

	Monthly Currency Excess Returns		
	(1)	(2)	(3)
HML Beta Loadings	RX1	RX1	RX1
OIL	0.171*	0.179*	0.184*
	(1.824)	(1.717)	(1.655)
VAL	-0.132	-0.111	-0.069
	(-0.404)	(-0.295)	(-0.168)
MOM3M		-0.065	0.153
		(-0.063)	(0.143)
CAR			0.449
			(1.356)
Constant	0.173**	0.149	0.181**
	(2.174)	(1.547)	(1.974)
Observations	8,681	8,681	8,681
R-squared	0.270	0.388	0.481
Number of groups	475	475	475

t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1

This table reports the Fama-Macbeth estimates to explain monthly currency excess returns by country oil imbalance controlling for carry, momentum, and value risk factors. The pricing factor carry (CAR) is the strategy that is long the 20% of forward discounts currencies and is short 20% of lowest forward discount currencies, both relative to the US. The pricing factor Momentum (MOM3m) is the zero-cost portfolio that is long the top 20% currencies with the highest 3 month-returns (winner currencies) and is short the bottom 20% currencies with the lowest 3 month-returns (looser currencies). The pricing factor value (VAL) is the zero-cost portfolio that is long the top 20% currencies with the highest five-year change in the natural logarithm of the real exchange rate (undervalued currencies) and is short the bottom 20% currencies with the lowest five-year change in the natural logarithm of the real exchange rate (overvalued currencies). OIL is the strategy that is long the top 20% of highest oil trade balance and is short the bottom 20% of lowest oil trade balance. We report Fama-MacBeth (1973) estimates market price of risk and the t-statistics in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level. Results rely on our main sample consisting of the 36 countries to construct the 4 pricing factors. It runs from October 1978 to August 2015. The portfolios are rebalanced monthly. Adjusted R2 is the average of the adjusted R2 in the cross sectional regressions over the sample period. Number of months represents the total cross-sectional panels (months) that are used to compute the estimators.

Table 6: Oil imbalance and financial characteristics to explain currency excess returns

	Monthly Currency Excess Returns				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	RX1	RX1	RX1	RX1	RX1
car	0.508***			0.703***	0.745***
	(10.688)			(8.918)	(10.374)
mom3m		0.233**		0.146	0.089
		(2.186)		(1.154)	(0.668)
val			0.494*	0.432	0.283
			(1.660)	(1.484)	(1.029)
oil					-0.086*
					(-1.773)
Constant	0.149	0.110	-0.017	-0.017	0.019
	(1.534)	(1.134)	(-0.132)	(-0.135)	(0.151)
Observations	8,681	8,663	6,257	6,255	6,255
R-squared	0.204	0.171	0.152	0.465	0.537
Number of groups	475	475	443	443	443

t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1

This table reports the Fama-Macbeth estimates for predictability of monthly currency excess returns using country oil imbalance, carry (car), momentum (mom3m), and value (val) as independent variables. Carry is defined as the forward discount $S_{j,t} - F_{j,t}$. Momentum is defined as the three-month change in the natural logarithm of the nominal spot exchange rate $S_{j,t} - S_{j,t-3}$. Value is defined as the five-year change in the natural logarithm of the real exchange rate $-(q_{j,t-12} - q_{j,t-60})$, which means that higher value indicates a weaker foreign currency. Oil imbalance (oil_imb) captures countries crude oil balance of trade in millions of tons. All variables are standardized in the cross-section in the form $(X_{j,t} - \mu_{Xj,t})/\sigma_{Xj,t}$. where $\mu_{Xj,t}$ is the average and $\sigma_{Xj,t}$ is the standard deviation of $X_{j,t}$ for the countries available in month t. Observations represent the total number of currencies included in the regressions over the sample period. Adjusted R2 is the average of the adjusted R2 in the cross sectional regressions over the sample period. The cross sectional regressions are conducted only where there are at least 10 country's data available in the month. Number of months represents the total cross-sectional panels (months) that are used to compute the estimators. t-statistics are reported in parentheses.

Table 7: Oil imbalance projection on carry trade

	Monthly Currency Excess Returns							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
res_oil_car	-0.07*	-0.07*	-0.09**	-0.08*	-0.08**	-0.06	-0.14***	-0.15***
	(-1.74)	(-1.75)	(-2.12)	(-1.77)	(-2.14)	(-1.53)	(-2.90)	(-2.71)
proj_oil_car					0.32***	0.34***	0.34***	0.27***
					(3.99)	(4.05)	(3.88)	(2.77)
mom3m	0.20*	0.08	0.09	0.03	0.07	0.02	-0.01	-0.07
	(1.70)	(0.63)	(0.73)	(0.28)	(0.52)	(0.15)	(-0.05)	(-0.49)
val	0.43	0.42	0.41	0.43	0.35	0.29	0.36	0.57*
	(1.30)	(1.41)	(1.31)	(1.32)	(1.25)	(1.08)	(1.27)	(1.65)
b_mom3m		-0.30*	-0.36**	-0.09		-0.23	-0.35*	-0.10
		(-1.71)	(-2.01)	(-0.42)		(-1.35)	(-1.93)	(-0.45)
b_val	-0.05		-0.06	-0.05	-0.20*		-0.24*	-0.23
	(-0.45)		(-0.48)	(-0.44)	(-1.66)		(-1.90)	(-1.64)
b_car				0.17*				0.17
				(1.96)				(1.65)
Constant	-0.05	-0.01	0.03	-0.08	0.03	0.12	0.12	-0.06
	(-0.38)	(-0.05)	(0.27)	(-0.56)	(0.26)	(0.96)	(0.96)	(-0.38)
Obs	6,255	6,255	6,255	6,255	6,255	6,255	6,255	6,255
R-squared	0.47	0.49	0.56	0.63	0.61	0.62	0.68	0.74
N. of months	443	443	443	443	443	443	443	443

t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1

This table reports the Fama-Macbeth estimates for predictability of monthly currency excess returns by the projection of the oil imbalance characteristic on carry controlled for financial characteristics carry, momentum, and value and their respective beta loadings. proj_oil_car is the projection of the oil characteristic on carry and res_oil_car is the orthogonal component. *t*-statistics are reported in parentheses.

Table 8: Beta versus characteristics - Individual currencies as test assets using Fama-MacBeth (1973)

	Monthly Currency Excess Returns					
	(1)	(2)	(3)	(4)	(6)	(7)
HML Beta Loadings	RX1	RX1	RX1	RX1	RX1	RX1
car	0.710***	0.745***	0.768***	0.684***	0.842***	
	(10.698)	(9.993)	(9.279)	(8.781)	(7.365)	
mom3m	0.065	-0.044	-0.071	-0.045	-0.171	
	(0.500)	(-0.319)	(-0.524)	(-0.349)	(-1.058)	
val	0.101	0.279	0.131	-0.315	-0.579*	
	(0.394)	(1.025)	(0.489)	(-1.081)	(-1.675)	
oil	-0.021	-0.105	0.059	-0.019	0.020	0.170***
	(-0.361)	(-1.559)	(0.864)	(-0.258)	(0.199)	(2.894)
b_OIL	-0.191	-0.102	-0.216	-0.074	-0.293	0.038
	(-1.443)	(-0.673)	(-1.567)	(-0.455)	(-1.640)	(0.303)
b_CAR		-0.223			-0.850	0.837**
		(-0.545)			(-0.843)	(2.359)
b_MOM3M			1.234		0.861	1.163
			(1.349)		(0.753)	(1.067)
b_VAL				-0.168	-0.915	0.210
				(-0.481)	(-1.004)	(0.507)
Constant	-0.053	0.063	0.030	0.087	0.106	0.209**
	(-0.422)	(0.489)	(0.233)	(0.701)	(0.445)	(2.265)
Observations	6,255	6,255	6,255	6,255	6,255	8,681
R-squared	0.615	0.694	0.682	0.684	0.814	0.512
Number of groups	443	443	443	443	443	475

This table reports the Fama-Macbeth estimates to explain monthly currency excess returns by beta loadings on global oil imbalance, carry, momentum, and value risk factors as well as oil imbalance, carry, momentum, and value characteristics. The pricing factor carry (CAR) is the portfolio that is long the 20% of forward discounts currencies and is short 20% of lowest forward discount currencies, both relative to the US. The pricing factor momentum (MOM3m) is the zero-cost portfolio that is long the top 20% currencies with the highest 3 month-returns (winner currencies) and is short the bottom 20% currencies with the lowest 3 month-returns (looser currencies). The pricing factor value (VAL) is the zero-cost portfolio that is long the top 20% currencies with the highest five-year change in the natural logarithm of the real exchange rate (undervalued currencies) and is short the bottom 20% currencies with the lowest five-year change in the natural logarithm of the real exchange rate (overvalued currencies). OIL is the strategy that is long the top 20% of highest oil trade balance and is short the bottom 20% of lowest oil trade balance. Car, mom3m, val and oil are the carry, 3-month momentum, value and oil trade imbalance characteristics, respectively. We report Fama-MacBeth (1973) estimates market price of risk and the t-statistics in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level. Results rely on our main sample consisting of the 36 countries to construct the 4 pricing factors. It runs from October 1978 to August 2015. Portfolios are rebalanced monthly.

Table 9: Double sorted portfolios – Characteristics vs Betas

		Monthly Currency Excess Returns		
		High Beta OIL	Low Beta OIL	HML Beta OIL
OIL Characteristic	High	0.215***	0.199*	0.016
		(2.587)	(1.799)	(0.150)
	Low	0.204*	0.011	0.193***
		(1.735)	(0.087)	(2.476)
	HML OIL Characteristic	0.011	0.188***	
		(0.098)	(2.902)	

This table reports the mean excess return and t-statistics for double sorted portfolios by characteristics and loadings. The characteristic considered is the oil balance of trade. We build the high-minus-low global oil imbalance risk factor and estimate currency betas on this factor using a time-series regression. We first split the sample of currencies at each month t in two halves (High and Low) with respect to the oil balance of trade characteristic, and within each of these into two halves (High and Low) with respect to the beta loading. The first two rows in each panel represent the mean of the equally weighted excess returns for countries with High and Low characteristics, respectively, over time, and the third row in each panel represents the difference in the mean of the equally weighted excess returns between the two groups. Similarly, the first two columns in each panel represent the mean of the equally weighted excess returns for countries with High and Low betas, respectively, over time and the third column in each panel represents the difference in the mean of the equally weighted excess returns between the two groups. t-statistics are reported in parentheses.

Chapter 4. Time-varying Arbitrage Capital and the Cross-Section of Stock Returns

Abstract

In this study, we explore the premise that the cross-section of return depends on arbitrage capital availability and that the abundance of arbitrage capital varies over time. We investigate the relationship between arbitrage capital, proxied by a market wide-liquidity measure introduced by Hu, Pan and Wang (2013), and the future performance of a set of eleven well-known pricing anomalies. When arbitrage capital is abundant, investors are able to deploy arbitrage strategies more successfully, which leads subsequently to lower future profitability of pricing anomalies. In contrast, when arbitrage capital is scarce, investors are unable to deploy enough capital to take advantage of pricing anomalies, yielding higher profitability of the anomaly strategies subsequently. Not only do we observe this pattern in the long leg and the short leg (opposite pattern) of the anomaly, but also in the long minus short decile strategy. Consequently, as a priced factor, time-varying arbitrage capital helps to explain the cross-sectional returns of pricing anomalies.

1. Introduction

Standard asset pricing theory is based on the idea that arbitrage capital rapidly flows toward any investment opportunity offering risk-adjusted returns, hence quickly eliminating these abnormal returns. Thus, the level of arbitrage capital available in the market has an impact on the asset prices. However, there is a growing body of literature on the limit of arbitrage that argues that frictions may prevent investors from fully eliminating asset mispricing. During ordinary times, institutional investors have abundant capital, which they can deploy to invest. Accordingly, price deviations from fundamental values are essentially eliminated by arbitrage forces, and assets are traded at prices close to their fundamental values. In periods of economic downturn, capital becomes scarce and ability to deploy it weakens, and liquidity in the overall market disappears. Diminution of arbitrage capital limits arbitrage forces and assets can be traded at prices significantly away from their fundamental values. Thus, in periods of economic uncertainty, asset pricing anomalies that are usually eliminated or mitigated by arbitrage forces may appear, persist and widen due to the shortage of arbitrage capital. In this paper, we analyze the effect of that time-varying arbitrage capital on anomaly performances in the equity market.

Abundance of arbitrage capital during normal times keeps the return of strategies based on well-known pricing anomalies close to what traditional asset pricing benchmarks (such as CAPM or Fama-French 3 or 5 factors models) predict. This is particularly true given the presence of factor investing hedge funds and trading desks focused on identifying and harvesting risk-adjusted alpha. For example, assets managed by hedge-funds taking advantage of so-called equity-market anomalies, such as value and momentum effects, grew from $101 billion in 2000 to $364 billion at the end of 2009 according to Lipper TASS Hedge Fund Asset Flows, a report quarterly published by Thomson Reuters. Nevertheless, during liquidity crises, the lack of arbitrage capital forces investment firms to limit or even abandon their anomaly based trading strategies, leaving asset prices moving more freely away from fundamentals. We argue that abundance of arbitrage capital impacts future performance of arbitrage driven anomaly strategies. When arbitrage capital is scarce, the future performance of pricing anomalies improves. When arbitrage capital is abundant, the future performance of pricing anomalies deteriorates.

To explore the impact of the abundance of arbitrage capital on asset prices, we examine a broad set of well-documented anomalies relative to the Fama and French (1993) three-factor model. We focus on equity strategies that exploit the cross-section of stock return anomalies uncovered over the last thirty years. These anomalies sort on characteristics that include idiosyncratic volatility, Amihud illiquidity, maximum return, gross margins, asset turnover, beta arbitrage, financial statement M-score, accrual volatility, financial health F-score, revenue surprise, change in forecast annual EPS and an equally weighted combination of these eleven pricing anomalies (called combination thereafter). For each anomaly, we examine the strategy that goes long in the stocks in the highest-performing decile and short in those in the lowest-performing decile, and the zero-cost long/short decile strategy that buys the highest-performing decile and sells the lowest-performing decile. These strategies generate abnormal risk-adjusted returns. There is a lively academic debate about whether these anomalies really represent alpha or whether they are instead compensation for other omitted risk factors or beta. We do not take a stand on this debate. Irrespective of whether anomalies represent mispricing or benchmarking errors, they provide a statistically reliable means of favorably biasing assessed performance against standard benchmarks. A skilled agent, such as hedge funds and arbitrage trading desks can be expected to exploit such an opportunity. We then use the noise illiquidity measure constructed by Hu *et al.* (2013) to explore the impact of time-varying arbitrage capital available on these pricing anomalies.

The measure of abundance of arbitrage capital is constructed by backing out a smooth zero-coupon yield curve using a popular function based model: Svensson (1994). This yield curve is then used to price all available bonds at a given point in time. For each bond, it is then possible to calculate the deviation between its market yield and the model yield. Aggregating the deviations across all bonds by calculating the root mean squared error, Hu *et al.* (2013) obtain a "noise". It is a measure of noise in the sense that deviations from a given pricing model are often referred to as noise in the fixed income literature. This noise measure is the proxy for capital arbitrage availability that we use.

The noise measure is an ideal candidate to depict the availability of arbitrage capital in the overall market for several reasons. The U.S. Treasury market is of primary importance and many types of investors come to this market to trade. Investors not only come for investment but also funding needs (used as collateral in short-term financing). Therefore, trading in the Treasury market holds information about liquidity needs for the broader financial market. Furthermore, the fundamental values of Treasury bonds are defined by a few interest rate factors. These interest rate factors can be easily backed out empirically. This provides a trustworthy benchmark to quantify price deviations, which provides pure information content relative to other markets (the equity market and corporate bond market among others) that may be informative, but contaminated by the existence of additional risk factors unlike the US treasury market. Finally, the US Treasury market is one of the most liquid markets in the world and boasts the highest credit quality. Therefore, it represents the first fly-to-quality market during crisis. A lack of liquidity in this market provides a resilient indication about liquidity in the overall market.

If frictions such as the lack of arbitrage capital are minor, then the excess returns to strategies that exploit anomalies should be insignificant (Lo 2004; Stein 2009). Conversely, if frictions such as the lack of arbitrage capital are more pronounced, it may hinder the extent to which pricing anomaly excess returns can be eradicated, even in the long run. These issues have been studied in the theoretical literature. However, empirical research investigating the relationship between arbitrage capital and returns has been hindered by a lack of appropriate proxy for arbitrage capital. In this paper, we propose to infer the predictability of anomaly returns given the amount of arbitrage capital available at a given time and document the relationship between the quantity of arbitrage capital and strategy returns. We find that abundance of arbitrage capital insures convergence to efficient price levels, leading to lower returns to the anomaly strategies in the future. In contrast, lack of arbitrage capital allows asset prices to deviate more freely from their fundamental value, leading to higher returns to the anomaly strategies in the future. These results provide a reasonable explanation for the persistence of cross-sectional return predictability. Whenever exogenous shocks push asset prices away from equilibrium, the presence of arbitrage capital is required in order to re-establish capital market efficiency. In absence of capital, deviation from fundamentals can persist.

This rest of the paper is structured as follows: section 2 provides the motivations and hypothesis, section 3 describes our data and the sample selection, section 4 provides the empirical results and discussion and section 6 concludes.

2. Motivations and hypotheses

Our paper contributes to the literature that explores the empirical implications of the theoretical limits of arbitrage and that stresses the connection between shortage of capital, market liquidity, and price deviations (Merton 1987; La Porta, Lopez-de-Silanes, Shleifer and Vishny 1997; Kyle and Xiong 2001; Gromb and Vayanos 2002). Merton (1987) questions the simplistic perfect-market assumption that firms can instantaneously raise sufficient capital to take advantage of profitable investment opportunities. He argues that practical implementations of trading strategies are neither costless nor instantaneous. He concludes that regulatory capital requirements and margin binding constraints may affect the short-run behavior of asset prices. La Porta *et al.* (1997) reinforce the notion that arbitrage activity requires capital and typically involves risk. He documents the asymmetric information problem between agents (fund managers) and principals (investors). This agency problem, known as performance-based arbitrage, may lead professional arbitrageurs to stay away from volatile arbitrage positions despite their attractive average returns. Hence, arbitrage capital is not flowing to these volatile, yet profitable positions keeping price away from their fundamentals. Coval and Stafford (2007) study equity fire sales by mutual funds and Mitchell, Pedersen and Pulvino (2007) on convertible bond arbitrage by hedge funds. Both of these studies provide additional empirical evidence on the relationship between arbitrage capital and price deviations. Brunnermeier and Pedersen (2009) relates market liquidity and availability of investors' capital. When funding liquidity is tight, investors become hesitant to take capital-intensive positions in high margin securities. They show that market liquidity is correlated across securities and can suddenly dry up due to uncertainty and volatility, which impacts asset prices. In Tuckman and Vila (1992), financial constraints arise from holding costs, and they prevent arbitrageurs from eliminating mispricings. In Dow and Gorton (1994), financial constraints take the form of a short horizon and a trading cost, and again mispricings arise. Yuan (2005) investigates a model in which arbitrageurs face a borrowing constraint. Gromb and Vayanos (2002) propose a model that capture systemic risk in which arbitrageurs supply liquidity. They find that a reduction in arbitrageurs' wealth can exacerbate the widening of the price wedge. Duffie (2010) describes a simple model of price dynamics triggered by the slow movement of investment capital to trading opportunities. This reflect institutional impediments to immediate trade, such as time to raise capital by intermediaries. The pattern of price responses to shocks produces a sharp reaction and a prolonged reversal, which induce temporary mispricing. Mitchell and Pulvino (2012) provide a detailed account of the financing of hedge funds during the 2008 crisis and its implications for asset prices. Nagel (2012) links the returns of short-term reversal strategies in equity markets with the expected returns from liquidity provision. Fleckenstein, Longstaff and Lustig (2010) document that the prices of nominal Treasury bonds and TIPS are inconsistent with inflation swaps and show a surge of this mispricing during the 2008 global financial crisis. Lou, Yan and Zhang (2013) find that anticipated Treasury auctions can engender temporary price deviations in the secondary market. Our study contributes to this literature by showing how the lack of arbitrage capital, another limit to arbitrage, impacts prices in the equity market.

In our study, we investigate the implications of time-varying abundance of arbitrage capital in anomaly strategies. Pricing anomalies provide a statistically reliable means of favorably biasing assessed performance against standard benchmarks. The literature on pricing anomalies is almost endless. A few empirical studies attempt to gather them (McLean and Pontiff 2016; Green, Hand and Zhang 2017, among others). Skilled investment managers can be expected to exploit such opportunities. In that regard, pricing anomalies constitute a conducive framework to examine the effect of forces driving asset prices. Stambaugh, Yu and Yuan (2012) explore sentiment-related overpricing using 11 pricing anomalies that survive adjustments for exposure to the three factors of Fama and French (1993). They find that the anomaly returns are stronger following high sentiment and that that the returns on the short leg portfolio of each anomaly is lower when sentiment is high. Edelen, Ince and Kadlec (2016) examine how institutional holding relates to a well-known source of return predictability using a set of 7 well-known pricing anomalies. They find that institutions have a tendency to buy stocks classified as overvalued. Hanson and Sunderam (2013) exploits the time-variation of the cross-section of short interest to infer the amount of capital allocated to equity pricing anomaly strategies. All of them adopt the consensus interpretation of the quantitative equity investors who believe that these anomalous return patterns predict stock returns (risk-adjusted or not) and therefore are conducive to conduct their respective studies. We adopt the same stand and we investigate the premise that time-varying arbitrage impacts asset prices, testing our hypotheses on a set of well-known pricing anomalies. Novy-Marx (2013) motivates this methodology, *"While I remain agnostic here with respect to whether these factors are associated with priced risks, they do appear to be useful in identifying underlying commonalities in seemingly disparate anomalies."* In this paper, the pricing anomalies are used as a useful signal to determine if the abundance of arbitrage capital is priced in the cross-section of stock returns.

Other studies investigate the asset pricing implications of liquidity and liquidity risk. We also contribute to this literature by testing the asset pricing implications of time-varying arbitrage capital using a noise illiquidity measure. Pástor and Stambaugh (2003) and Acharya and Pedersen (2005) document the liquidity pricing implications on equities and Bao, Pan and Wang (2011) conduct a similar investigation on corporate bonds. These studies focus on a specific market to both create and assess the liquidity risk measure. Hu *et al.* (2013) investigates the asset pricing implications of the noise liquidity measure on the carry strategy. Contrary to Hanson and Sunderam (2013), the arbitrage capital proxy we use is not restricted to the equity market and captures several market-wide liquidity dimensions, providing information beyond existing liquidity proxies. To the best of our knowledge, our study is the first one to test the implications of an overall market liquidity measure, which is not market specific, on pricing anomalies.

We use the "noise" liquidity measure developed by Hu *et al.* (2013), which captures the observed daily price deviation in U.S. treasuries from their theoretical value represented by the Svensson (1994) model. This model is an extension of the popular Nelson and Siegel (1987)'s forward rate function. Other function based model can be considered as potential candidates. For instance, Dahlquist and Svensson (1994) compare the original functional form of Nelson and Siegel (1987) to the more complex functional form of Longstaff and Schwartz (1992) on Swedish data for the sample period December 1992-June 1993. They conclude that the Nelson and Siegel (1987) functional form is easier to use than the Longstaff and Schwartz (1992) functional form. For this reason, in addition to its popularity as function-based models, the Svensson (1994) model is chosen. It provides additional flexibility by adding a fourth term with two additional parameters, β_3 and τ_2 and hence improves fit. Thus, the forward rate function can be written as:

$$f(T,v) = \beta_0 + \beta_1 \exp\left(-\frac{T}{\tau_1}\right) + \beta_2 \frac{T}{\tau_1} \exp\left(-\frac{T}{\tau_1}\right) + \beta_3 \frac{T}{\tau_2} \exp\left(-\frac{T}{\tau_2}\right),$$

Where $\mathrm{v} = (\beta_0,\ \beta_1,\ \beta_2,\ \tau_1,\ \beta_3,\ \tau_2)$ are model parameters to be estimated. $\beta_0,\ \beta_0 + \beta_1,\ \tau_1$ and τ_2 must be positive. *T* represents the forward maturity. There are four components. β_0 is a constant determined by taking the limit of m to infinity. The second term, $\beta_1 \exp\left(-\frac{T}{\tau_1}\right)$, is monotonically decreasing (or increasing if β_1 is negative) toward 0 as a function of the time settlement. The third and fourth terms generate two hump-shapes (or U-shapes depending of β_2 and β_3 signs) as a function of the time to settlement. As the forward maturity m approaches 0 (T → 0), f approaches to $(\beta_0 + \beta_1)$. In this model, β_0 represents the forward rate at infinitely long horizon while $(\beta_0 + \beta_1)$ represents the forward rate at maturity zero.

One can derive the zero-coupon yield curve solving the following optimization problem, using the parameterized forward curve:

Let K_t be the number of bonds and bills available on day t for curving fitting and let P_t^i be their respective market prices. The vector $\mathrm{v} = (\beta_0, \beta_1, \beta_2, \tau_1, \beta_3, \tau_2)$ is found by minimizing the weighted sum of the squared deviations between the model-implied and the actual price:

$$v_t = \underset{b}{\operatorname{argmin}} \sum_{i=1}^{K_t} \left[\left(P^i(b) - P_t^i \right) \times \frac{1}{D_i} \right]^2,$$

where D_i is the MaCaulay's duration for bond i.

The noise measure is constructed using the zero-coupon curve backed out from the daily cross-section of bonds. For each date t, p_t is the vector of model parameters backed out from the data. There are Kt Treasury bonds with maturity varying from 1 to 10 years. y_t^j is the market observed yield, and $y^j(v_t)$ is the model implied yield. As a measure of dispersion in yields around the fitted yield curve, the noise measure is built by computing the root mean squared error between the market yields and the model-implied yields:

$$Noise_t = \sqrt{\frac{1}{K_t}\sum_{j=1}^{K_t}\left[y_t^j - y^j(v_t)\right]^2},$$

where $Noise_t$ is the noise illiquidity measure, the arbitrage capital proxy that we use.

This measure captures liquidity risk of the entire market, focusing on the U.S. Treasury market. The U.S. treasury market is the market with the highest credit and liquidity quality. It reflects how different liquidity crises propagate to financial markets via movements of arbitrage capital. Rather than just measuring the liquidity of the treasury market, it is a reflection of the global market conditions. In general, liquidity may be driven by shocks in liquidity supply (market-makers and arbitrageurs), demand (transitory buyers and sellers) or both. Hence, a spike in the price noise of a particular security can come from an increase in liquidity demand, a decrease in liquidity supply, or both. However, shocks in liquidity demand of individual treasuries are averaged across a broad set of treasury security. Therefore, when arbitrage capital is abundant, it does not yield a peak in the noise measure. In contrast, shocks in liquidity supply do not only affect one asset but the universe of securities when there is a global shortage of arbitrage capital (or when market makers stop providing liquidity). Our study exploits the noise liquidity measure properties to help explain the return variations of pricing anomalies.

We formulate three hypotheses that we verify in our empirical section. Periods marked by high arbitrage flows are periods during which assets trade closer to their fundamentals. These periods are likely to exhibit a correction of cross-sectional mispricing, ensuing lower returns to the anomaly strategies in the future. Any mispricing that is present at the beginning of periods with low arbitrage capital is expected to persist the following period. Conversely, periods marked by lower arbitrage capital will be followed by periods with higher cross-sectional return predictability, which will manifest in the form of higher returns to the anomaly strategies. The preceding arguments suggest the following hypothesis:

H1: The performance of long minus short decile anomaly strategies is inversely related to the prior availability of arbitrage capital. Increase in noise liquidity measure is followed by higher profitability of the long minus short anomaly strategies.

H2: The performance of long leg anomaly strategies is inversely related to the prior availability of arbitrage capital. Increase in noise liquidity measure is followed by higher profitability of the long anomaly strategies.

H3: The performance of short leg of the anomaly strategies is positively related to the prior availability of arbitrage capital. Increase in noise liquidity measure is followed by higher profitability (lower returns) of the short anomaly strategies.

We test the above hypothesis and we find empirical support in our empirical section. Lower arbitrage flows, proxied by high noise liquidity measure, predicts higher future profitability of the long minus short, long and short anomaly strategies. This finding highlights the fact that market efficiency is a dynamic concept. Markets become more efficient due to the arbitrageurs' ability to intervene, itself dependent on the availability of arbitrage capital.

3. Data

3.1. Noise measure

We measure abundance of arbitrage capital using the daily noise measure constructed by Hu *et al.* (2013) and provided by their authors[45]. The noise measure spans over 27 years from 1987 to 2014. Therefore, our empirical analysis also goes from 1987 to 2014. The noise measure is constructed using a sample of Treasury bills, notes, and bonds that are non-callable, nonflowering, and with no special tax treatment. Bonds with maturity less than 1 month and longer than 10 years are excluded to avoid potential liquidity problems and lack of observations (making the fitted curve less reliable), respectively. The noise measure monthly average and standard deviation are 3.39 bps and 2.16 bps, respectively. The daily noise liquidity measure is plotted in figure 1. It appears to capture rather accurately fluctuations in liquidity shocks in the market. To name a few, the noise liquidity measure spikes to 13 bps during the October 1987 crash, it increases nearly to 6 bps during the LTCM crisis in September 1998, it peaks to 12 bps after September 9th, 2011. We observe similar jumps in noise the day following the sale of Bear Stearns to JP Morgan and the Lehman Brother default. Given the sample standard deviation, these events represent large deviations from the mean. It is interesting to observe the richness of the information content embedded in a variable that has been usually treated as pricing errors. When looking at daily observations, that are likely to be the most turbulent, we observe a high persistence of the measure quantified with a daily autocorrelation of 98.11%. This is comparable to the bid-ask spread yield of 2.1 bps for the same sample bonds, keeping the deviations unattractive

[45] We thank Grace Xing Hu for making the noise measure available on the personal website: http://www.sef.hku.hk/~gracexhu/NoiseUpdate_20150406.csv

for an arbitrageur trying to make a profit subject to transaction cost. This graphical illustration along with a few basic statistics show the informativeness and robustness of the measure. Because our central hypothesis revolves around the time-variation of available arbitrage capital, we examine the three-month change in noise measure rather than the level[46]. Since our study is conducted at monthly frequency, we calculate the last week of the month daily noise average[47]. Based on this constructed monthly noise measure, we compute the three-month change of noise, updated monthly. This variable is referred as *"noise"* in the rest of the paper.

3.2. Anomalies

We investigate previously documented pricing anomalies that survive adjustment for exposures to the three factors defined by Fama and French (1993) rather than the single-factor capital asset pricing model of Sharpe (1964). This benchmark imposes a higher hurdle but provides a large and diverse enough set of anomalies. To construct our sample of anomalies, we collect financial statements data from the Compustat North America annual and quarterly database (since certain anomalies require quarterly updating) as well as the I/B/E/S database. Following the pricing anomaly literature (Fama and French 1993; Edelen *et al.* 2016), we include domestic common shares trading on NYSE, AMEX, and NASDAQ that have a CRSP share code of 10 or 11 at the beginning of month t, good shares and price data at the beginning of t, and good return data for t. Throughout the analysis, we exclude micro-caps, defined as stocks with market value below the 20th NYSE percentile breakpoint following Fama

[46] We use three-month change to match the pricing anomalies frequency of update which are mostly accounting based.

[47] Using the last week average mitigates the potential inaccuracy of calculating the change of noise based a unique, end of the month, daily observation. Using an average of the daily noise observations across the entire month does not change the substance of our conclusions.

and French (2008).To avoid survivorship bias, we adjust monthly stock returns for delisting using the CRSP monthly delisting file following Shumway (1997). For the strategies using the annual files, accounting data for fiscal-year end of year t is matched with stock returns data from July of year t+1 until June of year t+2 to avoid look-ahead bias. For the strategies that use the quarterly files, the accounting data for a given quarter are matched to the end of the month in which they were reported (Novy-Marx 2016). Our final sample contains 635,877 firm-month observations.

We employ anomalies that are commonly used in the literature (Stambaugh *et al.* 2012; Lewellen 2014; Edelen *et al.* 2016; Green *et al.* 2017). We require each anomaly in the sample to exhibit a positive long minus short decile return spread in return in the period 1987-2014, statistically significant at least at 5% level. Our set includes anomalies used by Stambaugh *et al.* (2012), Lewellen (2014), Novy-Marx (2016) and Green *et al.* (2017). Our anomaly set includes beta arbitrage, asset turnover, idiosyncratic volatility, gross margins, maximum return, financial statement M-score, Piotroski's financial health F-score, revenue surprise, accrual volatility, illiquidity (bid-ask spread) and change in forecasted annual EPS. To form the anomaly returns, we sort the universe of stock based on the anomaly characteristic and allocate them in 10 decile portfolios each month. Anomaly portfolios are rebalanced monthly. All anomaly strategies consist of a monthly time-series of value-weighted returns. Taking value-weighted returns ensures that anomaly portfolio returns are not primarily driven by the performance of small market capitalization stocks. Portfolio 10 contains stocks expected to exhibit the highest returns based on the characteristic it was sorted on. Portfolio 10 will be called the long leg of pricing anomalies thereafter. Portfolio 1 contains stocks that are expected to exhibit the lowest returns based on the characteristic it was sorted on. Portfolio 1 will be called the short leg of pricing anomalies thereafter. We also define the zero-cost long/short portfolio that buys portfolio 10 and sells portfolio 1. This will be called the long-short anomaly portfolio thereafter. The 11 anomalies considered are presented in Table 1, along with their construction details and reference. When necessary, we control for the Fama and French (1993) three-factors (FF3 thereafter) we downloaded from Kenneth French's data library[48]: market excess return (MKT), size (SMB) and value (HML).

4. Empirical results and discussions

4.1. Summary Statistics

We document the magnitude and statistical significance of the excess-returns adjusted for the Fama and French (1993) three-factor model, or α_i, for each of the eleven anomalies. Table 2 – Panel B reports the α_i which are estimated in the following regression:

$$R_{i,t} = \alpha_i + bMKT_t + cSMB_t + dHML_t + u_{i,t},$$

where $R_{i,t}$ and $u_{i,t}$ are the excess-return and residuals, respectively, of the anomaly strategy i in month t, α_i is the intercept or risk-adjusted return of anomaly strategy i. MKT_t, SMB_t, HML_t are the time t returns of the market in excess of the one-month Treasury bill rate (from Ibbotson Associates), size and value long-short portfolios, respectively, available in Kenneth French's data library.

The Fama and French (1993) three-factor α_i are economically and statistically significant for all anomaly strategies at least at 5% level. The alphas range from 0.33% monthly (t -statistic = 2.06) for the change in forecasted earnings per share (EPS) anomaly to 1.08% monthly (t-statistic = 4.10) for the idiosyncratic volatility anomaly.

[48] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

The combination portfolio (Combination) that takes an equally-weighted position of all eleven anomalies earns a three-factor alpha of 0.59% (t -statistic = 4.35).

Table 1 – Panel A reports the correlation for the benchmark adjusted average returns, computed as the fitted values of $u_{i,t}$ in the regression:

$$R_{i,t} = \alpha_i + bMKT_t + cSMB_t + dHML_t + u_{i,t},$$

where $R_{i,t}$ and $u_{i,t}$ are the excess-return and residuals, respectively, of the anomaly strategy i in month t, α_i is the intercept or risk-adjusted return of anomaly strategy i. MKT_t, SMB_t, HML_t are the time t returns of the market in excess of the one-month Treasury bill rate (from Ibbotson Associates), size and value long-short portfolios, respectively, available in Kenneth French's data library.

This table is complemented by computing the variance inflation factor (VIF) from the time series regression of the long-short anomaly portfolios of 1-month ahead returns, reported in table 2 – Panel C and the principal component analysis reported in Table 2 – Panel D. The variance inflation factor quantifies the severity of multicollinearity in an ordinary least squares regression analysis. It provides an index that measures how much the variance of an estimated regression coefficient is increased because of collinearity. The square root of the variance inflation factor quantifies how much larger the standard error is compared with what it would be if the anomaly considered were uncorrelated with the other anomalies in the model. The average estimated variance inflated factor VIF($\hat{\beta}_i$) of our set of anomalies is equal to 2.51 and the maximum VIF($\hat{\beta}_i$)=7.3. Multicollinearity is considered to be high if VIF($\hat{\beta}_i$)>10. The VIF distribution does not suggest that multicollinearity is an issue in our set of anomalies.

Figure 2 shows the percentages of variance explained and eigenvalues of the anomalies long-short benchmark-adjusted returns explained by each of the 11 principal components. If the 11 individual strategies were completely orthogonal, we would witness a horizontal line centered at eigenvalue equal 1 and each component would explain 10.09% of variance. The first three principal components all have eigenvalues that exceed 1: 4.87; 2.32 and 1.25 therefore each of them explain more than 10.09% of variance. The percentages explained by the remaining seven components decay slowly. In table 2 panel A, the maximum return and the beta arbitrage strategies exhibit respectively the highest and lowest correlation with the equally weighted combination of all anomalies.

4.2. Average returns in low and high availability of arbitrage capital

We first categorize returns each month as a high or low of noise month. A high-noise month is one in which the value of the change of noise in the previous month is above the median value for the sample period, and the low-noise months are those in which the previous month change of noise is below-median values. We then compute risk-adjusted returns separately for the high- and low-noise months for each anomaly strategy. We conduct the analysis for the long, short and long minus short portfolios. We acknowledge that this empirical design induces a look-ahead bias by using the entire sample to determine periods of high and low noise. While this strategy may not work for real-time investments purpose, it may provide important empirical support about the informativeness of the noise measure we use. Table 3 reports results for returns adjusted by the FF3 benchmarks. The average returns in high- and low-noise periods are the estimates of a_H and a_L in the regression:

$$R_{i,t} = a_H d_{H,t} + a_L d_{L,t} + bMKT_t + cSMB_t + dHML_t + u_{i,t},$$

where $d_{H,t}$ and $d_{L,t}$ are dummy variables indicating high and low change in noise in month t-1. $R_{i,t}$ and $u_{i,t}$ are the excess-return and residuals, respectively, of the anomaly strategy i in month t. MKT_t, SMB_t, HML_t are the time t returns of the market in excess of the one-month Treasury bill rate (from Ibbotson Associates), size and value long-short portfolios, respectively, available in Kenneth French's data library.

Consider the first hypothesis, that anomaly strategies should have stronger average returns following high noise than following low noise. Tables 3 shows that each of the long-short spreads exhibits higher average profits following high noise. All of the values in the last column on the right, difference high minus low for the long-short strategies, are positive. Gross margin, idiosyncratic volatility and asset turnover anomalies all yield a difference larger than 0.65% per month while the lowest difference, 0.13% per month, is found for the financial statement F-score. The equally weighted combination of strategies earns 0.78% following high noise month with a t-statistic equal to 4.31 and 0.37% following low noise month with a t-statistic equal to 2.00. The high and low noise difference for the combination strategy is economically meaningful (0.40% monthly) and its t-statistics rejects the null hypothesis of no noise-related difference in favor of the one-sided alternative represented by the first hypothesis (one sided p-value = 0.056). More interestingly, we observe that 7 anomaly strategies become statistically insignificant in period of low noise, when arbitrage capital is abundant. These results are striking when compared to the FF3 risk adjusted returns pooling both period of high and low noise in table 2, in which all pricing anomaly strategies exhibit a large, strongly statistically significant spread. Nearly 2/3 of the anomalies' abnormal returns vanish when arbitrage capital is abundant, suggesting that a least some pricing anomalies appear in turbulent times, but do not exists in normal times. This finding is new to the literature and potentially opens new research avenues, investigating the conditional existence of pricing anomalies. Overall, the results in

Tables 3 provide strong support to the first hypothesis.

Next, consider the second hypothesis, which predicts that average returns on the long leg should be higher following high noise than following low noise month. In Tables 3, the long legs of 10-anomaly strategies out of 11 have higher average returns following high noise relative to low noise. The highest month return difference is found for revenue surprise (0.42%), accrual volatility (0.34%) and change in forecasted EPS (0.43%), while one anomaly strategy, beta arbitrage, shows a slightly negative monthly return difference (-0.08%). Finally, the long leg of the equally weighted strategy combining the 11 anomalies earns average returns of 0.55% (t-statistics 5.689) following high noise month while it earns average returns of 0.35% bps (t-statistics 4.075) following low noise months. Hence, the difference between the high minus low noise average returns is 0.20% per month. All but one high noise intercepts a_H are highly statistically significant rejecting the null hypothesis of no high noise effect return to the one-sided alternative (p-value=0.01). All but one low noise intercepts a_L are also highly statistically significant, rejecting the null hypothesis of no low noise effect on average return to the one-sided alternative. These results provide strong support to the second hypothesis, showing that anomalies' returns are stronger following periods of high noise relative to low noise.

The third hypothesis predicts that average returns on the short leg should be lower following periods of high noise relative to low noise. In Tables 3, 8 out of 11 anomaly strategies earn negative average monthly returns following high noise relative to low noise months. The asset turnover, idiosyncratic volatility and gross margins earn a high-low noise difference of -0.43%, -0.533% and -0.546%, respectively, exhibiting the lowest average excess returns in the sample. We notice that the 3 short leg anomaly strategies that do not display a negative difference high-low noise average returns are those that exhibit the strongest high-low noise difference in the long leg. Finally, the equally-weighted strategy combining the short leg of 11 anomalies earns average returns of -0.26% following high noise months while it earns average returns of -0.05% following low noise months. Hence, the difference high-low noise average return is -0.21% per month. Empirical evidences found in table 3 support hypothesis 3 showing that in the short leg, anomaly returns are lower following periods of high noise relative to low noise.

The evidence in table 3 appears to support the inference that noise-driven overpricing is at least a partial explanation for all of the anomalies analyzed in our study. Not only are the long-short anomaly strategies significantly stronger following high investor noise, but the long and the short legs separately are substantially more profitable in months following high noise.

4.3. Predictive regressions

The results reported above presents FF3 adjusted-returns in periods of high and low noise. In this section, we investigate an alternative empirical setting using predictive regressions to determine whether the noise predicts returns in ways consistent with our hypotheses. While the section 4.3 uses the entire sample to classify time periods into high or low noise, this section presents predictive evidence that could have been used for real time investment. Table 4 reports the estimates of b_i resulting from the ordinary least squared (OLS) regression of anomaly i excess-returns on the lagged noise measure:

$$R_{i,t} = a_i + b_i N_{t-1} + u_t,$$

where $R_{i,t}$ and $u_{i,t}$ are the excess-return and residuals, respectively, referring to anomaly strategy i in month t, a_i is the intercept relative to anomaly strategy i. N_{t-1} is the noise measure at month t-1.

This regression thus investigates the ability of noise measure to predict excess-returns. The first hypothesis (long-short anomaly strategies are stronger following periods of high noise) predicts a positive relation between the profitability of each long-short spread and the noise measure. Consistent with this prediction, the slope coefficients for the spreads of all anomalies are positive and strongly statistically significant in Tables 4. The highest estimated slopes are obtained for beta arbitrage (0.758), idiosyncratic volatility (0.863) and Amihud illiquidy (0.831) strategies. The lowest estimated slope is obtained for the financial M-score (0.303) strategy and remain significantly positive, both economically and statistically. The slope of the combination (0.501) strategy is significant, both economically and statistically at 1% level. In other words, a change of noise of +1 basis point results in an increase of excess-returns of the equally weighted combination of the 11 long-short strategies by 0.501 basis point.

The second hypothesis (the long leg of anomalies is stronger following periods of high noise) predicts a positive relation between the profitability of each long leg and the noise measure. Results are not consistent with our hypothesis as the estimated slopes on the long legs are all negative. In this regression, we do not control for market-excess returns (and the two other FF3 factors). It is likely that periods of noise increased are followed by negative shocks in the equity market (see figure 1). In that sense, our specification may suffer from severe omitted variable bias if we do not include market-excess returns. We run the same regression including the excess-market returns (and the two others FF3 factors) to confirm this hypothesis. Results are presented in the next paragraph (Table 5).

The third hypothesis (short leg anomaly strategies exhibit lower returns following periods of high noise) predicts a negative relation between the returns of each short leg and the noise measure. In other words, the profitability of short-selling the short leg is higher following periods of high noise. Consistent with this prediction, the slope coefficients for the spreads of all anomalies are all negative and strongly statistically significant beyond 1% level in Tables 4. The lowest estimated slopes are obtained for beta arbitrage (-1.050), idiosyncratic volatility (-1.135) and Amihud illiquidity (-1.113) strategies. The highest estimated slope is obtained for the accrual volatility (-0.601) strategy and remains significantly negative, both economically and statistically at 1% level. The slope of the combination (-0.878) strategy is significantly negative, both economically and statistically at 1% level. In other words, a change of noise of +1 basis point results in a decrease of excess-returns of the equally-weighted combination of the 11 short strategies by -0.878 basis point. Considering the omitted variable bias we suspect, we will also confirm the robustness of these results in table 5.

To confirm the robustness of our results, we reiterate the OLS regression conducted in the previous paragraph controlling for the FF3 factors. Table 5 reports the estimates of *b* resulting from the OLS regression of excess-returns on the lagged change of noise measure as well as the FF3 factors:

$$R_{i,t} = a + bN_{t-1} + cMKT_t + dSMB_t + eHML_t + u_t$$

where $R_{i,t}$ and $u_{i,t}$ are the excess-return and residuals, respectively, referring to anomaly strategy i in month t, a_i is the intercept relative to anomaly strategy i. N_{t-1} is the noise in month t-1.

This regression thus investigates the ability of noise measure to predict FF3-adjusted returns. The first hypothesis (long-short anomaly strategies are stronger following periods of high noise) predicts a positive relation between the profitability of each long-short spread and the change of noise measure. Consistent with this prediction, the slope coefficients for the spread of all anomalies except one are positive and statistically significant in Tables 5. The highest estimated slopes are obtained for beta arbitrage (0.504), idiosyncratic volatility (0.655), maximum return (0.528) and Amihud illiquidy (0.623) strategies. The lowest estimated slope is obtained for the financial M-score (-0.007) strategy which is not statistically significant. The slope of the combination strategy (0.346) is significantly positive, both economically and statistically at 1% level. In other words, a change of noise of +1 basis point results in an increase of FF3-adjusted returns of the equally weighted combination of the 11 long-short strategies by 0.346 basis point.

The second hypothesis (the long leg of anomalies are stronger following periods of high noise) predicts a positive relation between the profitability of each long leg and the noise measure. These results are important and interesting since we do not find consistent evidence to the hypothesis 2 in table 4. We expect the potential omitted variable problem to be mitigated controlling for the FF3 factors. By and large, results in Table 5 confirm the omitted variable problem discussed in Table 4. Controlling for the FF3 factors, in particular excess market returns, changes the sign of all but on estimated from negative to positive. Nine of the anomalies present a positive slope that is statistically significant. The combination strategy presents a positive slope (0.121) that is statistically significant at 1% level. After controlling for the FF3 factors, a change of noise of +1 basis point is followed by an increase in the combination strategy benchmark-adjusted excess returns of 0.121 basis points.

The third hypothesis (short leg anomaly strategies exhibit lower returns following periods of high noise) predicts a negative relation between the returns of each short leg and the noise measure. In other words, the profitability of short-selling the short leg is higher following periods of high noise. Consistent with this prediction, the slope coefficients for the FF3 adjusted returns of all anomalies are negative. Eight of them are statistically significant in Tables 5. The lowest estimated slopes are obtained for the idiosyncratic volatility (-0.519), maximum return (-0.411) and Amihud illiquidity (-0.507) strategies. The highest estimated slope is obtained for the financial M-score (-0.001) strategy and remains negative. The slope of the combination (-0.225) strategy is significantly negative, both economically and statistically at 1% level. In other words, a change of noise of +1 basis point results in a decrease of FF3 adjusted-returns of the equally-weighted combination of the 11 short strategies by -0.225 basis point. These results strongly support that hypothesis that short leg anomaly strategies exhibit lowest returns following periods of high noise after controlling for the FF3 factors.

In sum, results from the predictive regressions reported in tables 4 and table 5 deliver the same message as the results comparing returns following high and low noise periods presented in Tables 3. The data support a scenario in which the lack of capital arbitrage prevents investors from taking advantage of the well know pricing anomalies, generating abnormal returns in the subsequent period. This assessment holds for the long leg, the short leg (lower returns) and the long-short decile strategies. The lack of arbitrage capital appears to be at least a partial explanation for the broad set of anomalies examined in our study.

4.4. Newey-West Lags

In our application of the Newey-West estimation procedure, we use a lag of 5 for the results tabulated in this paper, which we obtain following the rule of thumb in, for example, Greene (2003), by calculating $T^{0.25}$, where T is the number of observations. Since our sample consists of 332 observations, the appropriate number of lags according to the rule of thumb is 4 or 5. We choose 5 to be conservative. The Newey-West (1987) approach is consistent, which means that by letting the number of lags grow with longer samples, we should eventually get the right standard error. If too few lags are used, standard errors are biased and regressions may be spurious. In order to test the robustness of our results, we run all regressions again changing the number of lags from 0 to 4. The statistical significance of our results tend to improve as the number of lags decrease. Most importantly, our conclusions remain unchanged and hence do not depend on the number of lags chosen.

5. Robustness test: control for additional variables

5.1. Horse race between noise and Baker and Wurgler (2006) investor sentiment index

Stambaugh *et al.* (2012) explores the role of investor sentiment in a similar set of anomalies in the equity market. They argue that the presence of market-wide sentiments influence subsequent returns. In their empirical setting, they claim that high sentiment exacerbates overpricing. They use the Baker and Wurgler (2006) sentiment index (BW subsequently) to explain the spread of the long-short set of anomalies. They also claim that returns in the short leg should be lower following a month of high sentiment due to short-sale impediments. Finally, they argue that *sentiment* have no impact on the long leg.

In this section, we investigate the role of the abundance of arbitrage capital relative to the BW sentiment index. In particular, we want to verify the robustness of our results and confirm the role of arbitrage capital in the performance of pricing anomalies in the equity market after controlling for the BW market sentiment index. To assess the relative importance of investor sentiment relative to the abundance of arbitrage capital, we run a horse race between the BW sentiment index and the noise measure. We download the BW investor sentiment data on Jeffrey Wurgler's webpage[49]. The time

[49] http://people.stern.nyu.edu/jwurgler/

series available on his website covers the entire time span of our study. More specifically, we employ the composite index constructed by taking the first principal component of six measures of investor sentiment, which is the exact same measure employed by Stambaugh *et al.* (2012). Hence, we run the following time-series regression:

$$R_{i,t} = a + bN_{t-1} + cS_{t-1} + u_t,$$

where $R_{i,t}$ and $u_{i,t}$ are the excess return and residuals, respectively, referring to anomaly strategy i in month t, a_i is the intercept relative to anomaly strategy i. N_{t-1} is the noise measure in month t-1 and S_{t-1} is the three-month BW investor sentiment change in month t-1, called *"sentiment"* measure thereafter.

Table 6 reports the slope coefficients b and c, and their respective statistical significance. First, we consider the results obtained on the long-short anomaly strategies. The slope coefficients on the noise measure are all positive and strongly statistically significant at 1% or 5% level. In contrast, the slope coefficients on the sentiment index are all statistically insignificant. Two of them have a negative sign. For the combination strategy, the coefficient on noise (0.523) is positive and statistically significant at 1%, where the slope coefficient on investor sentiment is statistically insignificant. These results show that the noise measure subsumes the sentiment index, which implies that the abundance of arbitrage capital affects future performance of anomalies and investor sentiment does not. Similar conclusions can be drawn for the long and short leg of anomalies. We find that the noise measure subsumes the sentiment index both of the long and short leg. All slope estimates on the noise measure are statistically significant at 1% level in the short leg and at 1% or 5% in the long leg. The slopes on noise measure are negative both in the long and short leg, consistent with estimates we found in table 4. We conclude that the noise measure subsumes the investor sentiment index in the long and short legs too.

As an additional robustness test, we run the same time-series regression controlling for the FF3 factors:

$$R_{i,t} = a + bN_{t-1} + cS_{t-1} + bMKT_t + cSMB_t + dHML_t + u_{i,t},$$

where $R_{i,t}$ and $u_{i,t}$ are the excess return and residuals, respectively, referring to anomaly strategy i in month t, a_i is the intercept relative to anomaly strategy i. N_{t-1} is the noise measures in month t-1 and S_{t-1} is the sentiment measure in month t-1.

Table 7 reports the slope coefficients b and c, and their respective statistical significance. First, we consider the results obtained on the long-short anomaly strategies. The slope coefficients on the noise measure are all positive and statistically significant beside that of financial statement M-score. In contrast, the slope coefficients on the sentiment index are all statistically insignificant. Three of them have a negative signs. For the combination strategy, the coefficient on noise (0.351) is positive and statistically significant at 1%, where the slope coefficient on investor sentiment is statistically insignificant. These results show that the noise measure subsumes the sentiment index even after controlling for the FF3 factors, which implies that the abundance of arbitrage capital affect future performance of anomalies and investor sentiment does not.

Similar conclusions can be drawn for the long and short leg of anomalies. We find that the noise measure subsumes the sentiment index both of the long and short leg although certain slope estimates lose their statistical significance after controlling for the FF3 factors. In the short leg, eight slope estimates are negative as expected and statistically significant. In the long leg, eight slope estimates on noise are statistically significant, and, more interestingly, the sign becomes positive for all of them but one. This change of sign is consistent with the results found in table 5 and our hypothesis 2 that concludes that future performance of the long leg improves as noise increases.

Results in tables 6 and 7 are strong support to our first hypothesis that states that a shortage of arbitrage capital improves the future performance of the long-short anomaly strategies whereas the BW (2006) investor sentiment has no impact after controlling for the abundance of arbitrage capital. We can also conclude that a shortage of arbitrage capital has a positive impact on the future performance of the long and the short legs of anomaly strategies, which support our hypotheses 2 and 3. After controlling for the abundance of arbitrage capital, we find no evidence that investor sentiment index plays a role in explaining the long-short and short leg return variations of anomalies in the equity market as claimed by Stambaugh *et al.* (2012). However, we confirm that BW (2006) investor sentiment index does not play a role in explaining the long leg return variations of anomalies as described by these authors.

5.2. Additional controls: macroeconomic variables

To assess the potential for a risk-based explanation, we control for a set of macro-related variables potentially correlated with a risk premium. In particular, we include the six macro-variables from Baker and Wurgler (2006): the growth in employment, the growth in durable consumption, the growth in non-durable consumption, the growth in services consumption, the growth in industrial production and a recession indicator from the National Bureau of Economic Research. Additionally, we control for the same five macro-variables included in Stambaugh *et al.* (2012): the consumption-wealth ratio (cay), the real interest rate, the term premium, the default premium and the inflation rate.

$$R_{i,t} = a_i + b_i N_{t-1} + \sum_{k=1}^{9} m_{i,k}\, Macro_{k,t-1} + d_i MKT_t + e_i SMB_t + f_i HML_t + u_{i,t},$$

where $R_{i,t}$ and $u_{i,t}$ are the excess return and residuals, respectively, referring to anomaly strategy i in month t, a_i is the intercept relative to anomaly strategy i. N_{t-1} is the noise measure in month t-1, $Macro_{k,t-1}$ represents the macroeconomic control variable k in period t-1.

The real interest rate is constructed as the most recent monthly difference between the 30-day T-bill return and the consumer price index inflation rate. The term premium is defined as the spread between 10-year and 1-year Treasuries. The default premium is the yield spread between BAA and AAA bonds, and cay is the consumption-wealth ratio from Lettau and Ludvigson (2001).

Table 8 – Panel A, B and C reports the results of regressing excess returns on the lagged noise measure, the contemporaneous returns on the FF3 factors, and the eleven contemporaneous macro-related variables for the long-short, long and short legs of each anomaly. Thus, we assess the noise measure predicting power after controlling for macro-related fluctuations. The effects of the noise liquidity measure remain largely unchanged by including the additional eleven variables in the long-short, long and short legs. All estimates on noise are positive and most of them statistically significant when predicting the long-short and long leg anomaly returns. Estimates on noise are all negative and most estimates are statistically significant when predicting short leg anomaly returns. The coefficient on noise for the combination strategy is statistically significant at 1% level for the long-short (positive), long (positive) and short (negative) strategy after controlling for the 11 macroeconomic variables. It is interesting to note that most estimates are close to those in Table 5, in which the additional macro-related

variables are not included. Overall, we demonstrate the anomalies considered at least partially reflect mispricing that is related to the noise measure. The results disclosed from Table 3 to Table 8 confirm that the performance of long minus short decile anomaly strategies is inversely related to the prior availability of arbitrage capital flow. Increase in noise liquidity measure is followed by higher profitability of the long minus short anomaly strategies.

Table 3, 4, 5, 6, 7 and 8 Panel A validate this hypothesis. Dividing the sample in high and low noise periods, the “Long-Short” result columns in table 3 show that the profitability of the long minus short anomaly strategies are higher following high noise periods in the 12 anomalies considered. In particular, following high noise, each anomaly displays strong positive and statistically significant excess returns. This inference is confirmed by the straightforward OLS results (with and without control variables) presented in table 4 and 5. In these tables, excess returns of the long-short strategies are all (but one) positive and statistically significant, showing that a noise increase in period t induces higher returns in period t+1. These conclusions are robust after controlling for the Baker and Wrugler (2006) sentiment index (including and excluding control variables). In fact, in table 6 and 7, the BW (2006) sentiment index is subsumed by the strong explanatory power of the noise measure in the long minus short decile of each strategy, supporting further the main hypothesis. Finally, it seems reasonable to expect anomaly performances to be correlated with some aspect of macroeconomic conditions. In Table 8, we control for an additional set of 11 macro-related variables that seem reasonable to entertain as being correlated with anomaly performances. Conclusions remain consistent with previous findings as all but 1 noise measure coefficients are positive and statistically significant, supporting the idea that future long minus short strategy returns increase with noise. All in all, different empirical designs provide strong consistent evidence across strategies and anomalies giving us confidence that arbitrage capital flow proxied by the noise measure plays a central role in explaining anomalies excess returns.

However, this study does not aim to find complete explanations for each of the anomalies considered. Numerous studies examine the individual anomalies in more detail and provide more specifically focused contexts and interpretations. We paint the set of anomalies with an intentionally broad brush, given our objective to consider the implications when time-varying arbitrage capital flow interact with pricing anomalies. Our objective is to explore the possibility that arbitrage capital flow plays a pervasive role over time in affecting the degree of mispricing that arises in a broad range of specific contexts. In the cross section, we do not attempt to add explanations for why greater mispricing is associated with more extreme values of a particular characteristic used to produce an anomaly. While this approach reveals novel evidence consistent with overpricing as at least a partial explanation for many anomalies, certainly more work lies ahead to develop a richer understanding of how arbitrage capital flow plays a role in pricing financial assets.

6. Conclusion

We document a negative relation between time-varying arbitrage capital and future returns of anomalies in the equity market. Abundance of arbitrage capital insures convergence to efficient price levels, leading to lower returns of the anomaly strategies in the future. In contrast, lack of arbitrage capital allows asset prices to deviate more freely from their fundamental values, leading to higher returns of the anomaly strategies in the subsequent period. Whenever exogenous shocks push asset prices away from equilibrium, the abundance of arbitrage capital is required to re-establish capital market efficiency. In absence of arbitrage capital, the long-short anomaly spread persists or widens. Conversely, if arbitrage capital were to become unlimited and freely available at all times, the long-short anomaly spread would shrink, impacting future predictability. Pricing anomalies are likely to exhibit time-varying performance as long as the availability of arbitrage capital is time-varying. Our study opens new opportunities for future research. For instance, the impact of time varying-capital on the cross-section of stock returns outside the U.S. remains an unanswered question. Lower or different accounting standards, less transparent markets or the lack of data may deter arbitrageur to deploy sufficient arbitrage capital. It would be interesting to investigate the impacts of time-varying arbitrage capital on such markets.

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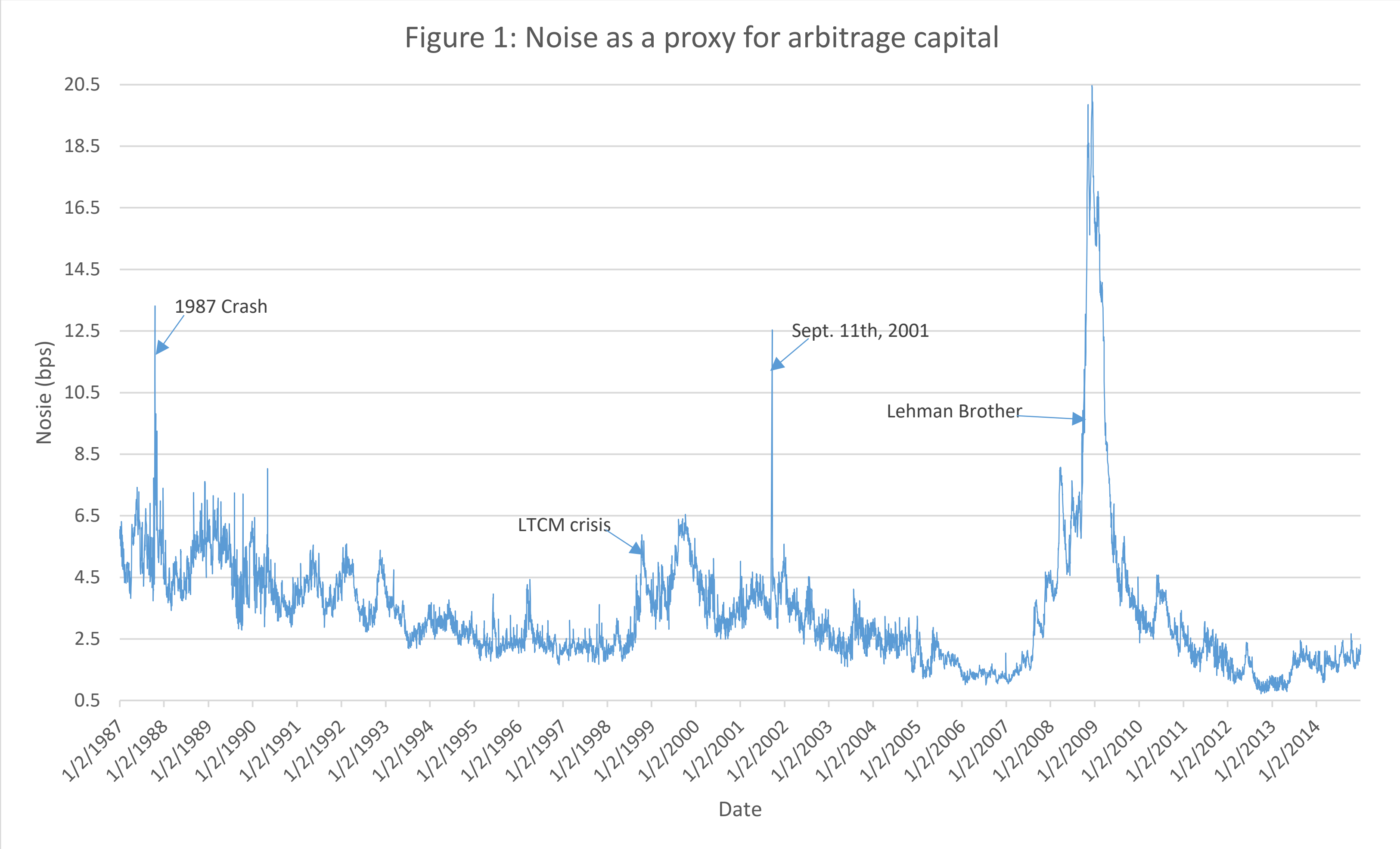
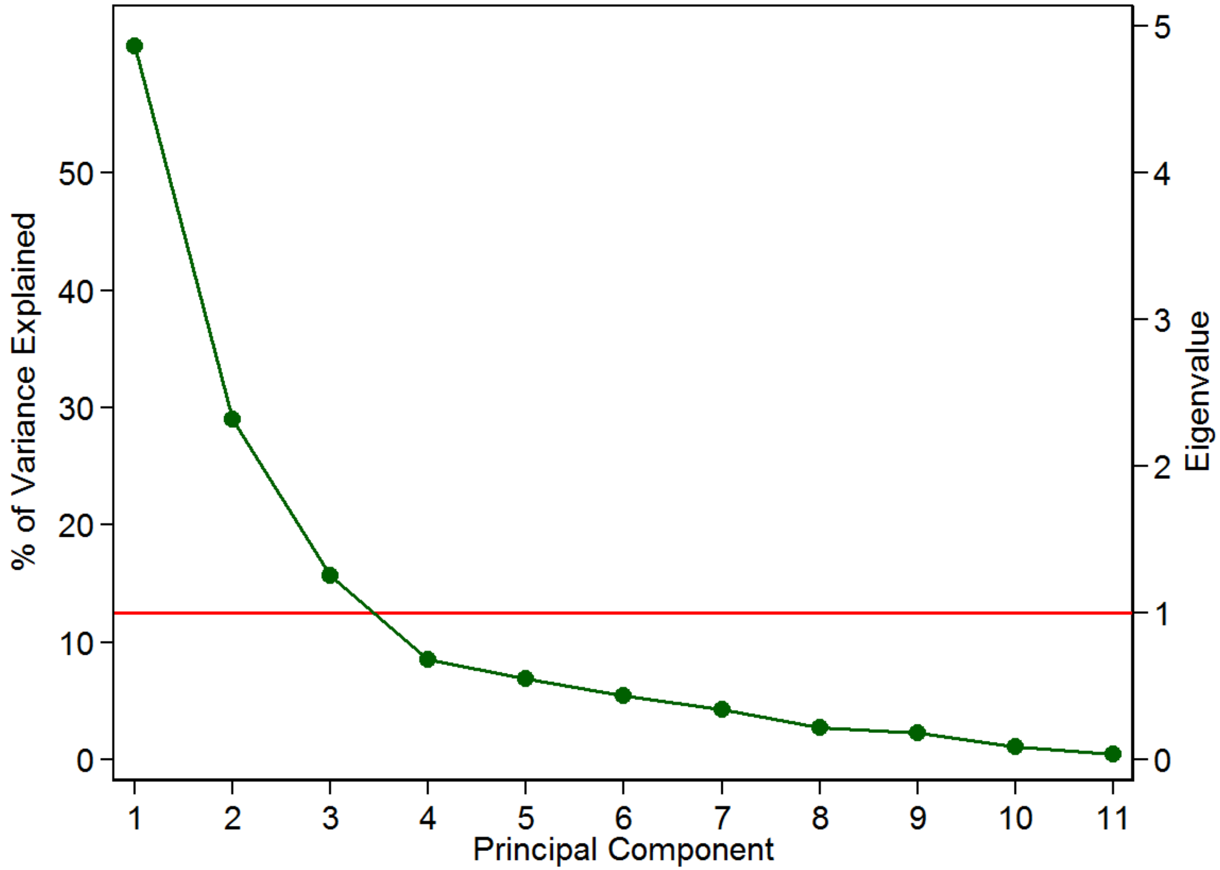


Figure 1: Time-series of the daily noise measure in basis points including key liquidity shocks.

Figure 2: Principal Component Analysis



Percentage of variance explained by eigenvalues and principal components. The figure display the percentage of variance explained by the principal components of the benchmark-adjusted long-short spreads ranked by eigenvalue from the biggest (Component 1) to the smallest (Component 11). The red line at 10.09% is the percentage of variance explained by each principal component if the 11 long-short spreads were uncorrelated with each other.

Table 1: Anomalies Considered

Anomaly	Description	Citation
Beta Arbitrage	Firms are sorted based on their estimated market beta, and then hedged for their market exposure using rolling betas estimated from the previous year's daily returns.	Black (1972) and Frazzini and Pedersen (2014)
Asset Turnover	Asset Turnover = SALE/AT, where SALE is total sales and AT is total assets.	Novy-Marx (2013)
Idiosyncratic Volatility	In each month, firms are sorted based on the standard deviation of the residuals of regressions of their past three months' daily returns on the daily returns of the Fama-French three factors.	Ang, Hodrick, Xing and Zhang (2006)
Gross Margins	Gross Margins = GP/SALE, where GP is gross profits and SALE is total sales.	Novy-Marx (2013)
Maximum Return	Maximum daily return in prior month	Bali, Cakici and Whitelaw (2011)
Financial Statement M-score	Sum of 9 indicator variables that form fundamental performance measure M-score.	Mohanram (2005)
Financial Health F-score	Sum of 9 indicator variables that form fundamental financial health F-score.	Piotroski (2000)
Revenue Surprise	Sales from quarter t minus sales from quarter t-4 (saleq) divided by fiscal quarter end market cap (cshoq * prccq).	Kama (2009)
Accrual Volatility	Standard deviation for 16 quarters of accruals scaled by sales. Accruals is defined as change in non-cash current assets minus change in current liabilities minus change in debt in current liabilities (change in actq minus change in cheq minus change in lctq plus change in dlcq). If item is missing it is set to zero. Change is for 1 quarter change.	Bandyopadhyay, Huang and Wirjanto (2010)
Illiquidity	Monthly average of daily bid-ask spread divided by avg of daily bid-ask spread.	Amihud and Mendelson (1989)
Change in Forecasted Annual EPS	Mean analyst forecast of annual EPS in month prior to fiscal period end date from IBES summary file minus same mean forecast for prior fiscal period.	Hawkins, Chamberlin and Lanstein (1985)

Table 2. Descriptive Statistics

Panel A: Correlations

Anomaly	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	1											
(2)	0.14*	1										
(3)	0.82***	0.21***	1									
(4)	0.037	0.78***	0.14*	1								
(5)	0.76***	0.22***	0.93***	0.18**	1							
(6)	-0.27***	0.32***	-0.14*	0.39***	-0.15**	1						
(7)	0.36***	0.48***	0.42***	0.45***	0.46***	0.039	1					
(8)	0.36***	0.28***	0.40***	0.22***	0.42***	-0.21***	0.47***	1				
(9)	0.37***	0.55***	0.48***	0.62***	0.53***	0.15**	0.36***	0.30***	1			
(10)	0.85***	0.22***	0.95***	0.12*	0.88***	-0.20***	0.37***	0.41***	0.49***	1		
(11)	0.26***	0.11*	0.34***	0.083	0.27***	-0.17**	0.32***	0.50***	0.048	0.34***	1	
(12)	0.76***	0.57***	0.87***	0.51***	0.86***	0.036	0.63***	0.57***	0.70***	0.86***	0.43***	1

(1) Idiosyncratic Volatility
(2) Illiquidity
(3) Maximum Return
(4) Gross Margins
(5) Asset Turnover
(6) Beta Arbitrage
(7) Financial Statement M-score
(8) Accrual Volatility
(9) Financial Health F-score
(10) Revenue Surprise
(11) Change in Forecasted Annual EPS
(12) Combination

The table reports correlation of benchmark-adjusted average returns for the 11 anomalies and an equally-weighted combination of them. The sample period is from 1987:4 to 2014:12 for all anomalies except the change in forecasted annual EPS for which analyst forecasts only starts in 1989:01. Residuals are computed as the fitted values of $u_{i,t}$ in the regression:

$$R_{i,t} = a + bMKT_t + cSMB_t + dHML_t + u_{i,t}$$

where $R_{i,t}$ is a strategy's excess return over the one month risk free rate in month t. t statistics shown underneath the estimated coefficients are based on Newey and West (1987) heteroskedasticity and autocorrelation-consistent standard errors. ***, **, and * indicate two tailed statistical significance at levels 0.1%, 1%, and 5%, respectively.

Panel B: Long minus short benchmark-adjusted returns

Anomalies	Long-Short FF3 α	t-statistic	Observations
Combination	0.59***	(4.35)	336
Beta Arbitrage	0.62**	(2.06)	336
Asset Turnover	0.51**	(2.30)	336
Idiosyncratic Volatility	1.08***	(4.10)	336
Gross Margins	0.40**	(1.98)	336
Maximum Return	0.81***	(3.62)	336
Financial Statement M-score	0.47***	(3.55)	336
Financial Health F-score	0.42***	(4.00)	336
Revenue Surprise	0.46***	(3.03)	336
Accrual Volatility	0.42**	(1.92)	336
Illiquidity	0.95***	(3.13)	336
Change in Forecasted Annual EPS	0.33**	(2.06)	312

The table presents average monthly returns in percent for all the anomaly portfolios and their equally-weighted combination, between 1987:04 and 2014:12 exept the change in forecasted annual EPS for which analyst forecasts only starts in 1989:01. Anomaly portfolios are formed by ranking on the indicated variable each month and taking a long (short) position in the highest (lowest) performing decile. The position is held for one month. Monthly three-factor alpha (%) refers to the intercept from a time-series regression of monthly value-weighted excess returns$R_{i,t}$ on the MKT_t, SMB_t, and HML_t factors:

$$R_{i,t} = a + bMKT_t + cSMB_t + dHML_t + u_{i,t}$$

t-statistics shown next to the estimated coefficients are based on Newey and West (1987) heteroskedasticity and autocorrelation-consistent standard errors. ***, **, and * indicate one tailed statistical significance at levels 1%, 5%, and 10%, respectively.

Panel C

Table 1 B: Variance Inflation Factor

Variable	**VIF**	**1/VIF**
Idiosyncratic Volatility	7.3	0.14
Illiquidity	4.67	0.21
Maximum Return	3.63	0.28
Gross Margins	2.46	0.41
Asset Turnover	2.29	0.44
Beta Arbitrage	1.51	0.66
Financial Statement M-score	1.37	0.73
Accrual Volatility	1.23	0.82
Financial Health F-score	1.09	0.92
Revenue Surprise	1.06	0.94
Change in Forecasted Annual EPS	1.01	0.99
Mean VIF	2.51	

Variance inflation factors (VIF) from the time-series regression of the long-short anomaly portfolios of 1-month ahead returns.

Panel D

Table 1 - Panel D: Principal Component Analysis (PCA)

Component	**Eigenvalue**	**Portion Variance Explained**	**Cumulative Variance Explained**
Comp1	4.87	44.2%	44.2%
Comp2	2.32	21.1%	65.4%
Comp3	1.26	11.5%	76.8%
Comp4	0.68	6.2%	83.0%
Comp5	0.56	5.1%	88.1%
Comp6	0.44	4.0%	92.1%
Comp7	0.34	3.1%	95.2%
Comp8	0.22	2.0%	97.2%
Comp9	0.19	1.7%	98.9%
Comp10	0.09	0.8%	99.7%
Comp11	0.04	0.3%	100.0%

The table reports the eigenvalues, percentage and cumulative percentage of variance explained by the principal components of the eleven benchmark-adjusted long-short spreads. The fraction of variance explained by the *n*th principal component is the *n*th largest eigenvalue of the correlation matrix divided by the number of components (11 anomalies). The green line drawn at eigenvalue equal one would be the percentage of variance explained by each principal component if all anomalies were uncorrelated with each other.

Table 3: Anomaly performance following periods of high and low noise: benchmark-adjusted returns on long-short strategies

Anomaly	Long Leg			Short Leg			Long-Short		
	High Noise	Low Noise	Difference High-Low	High Noise	Low Noise	Difference High-Low	High Noise	Low Noise	Difference High-Low
Combination	0.549***	0.353***	0.20	-0.258**	-0.048	-0.210	0.782***	0.378**	0.40
	(5.689)	(4.075)		(-2.135)	(-0.314)		(4.310)	(2.007)	
Beta Arbitrage	0.411***	0.487***	-0.08	-0.377	-0.022	-0.354	0.763**	0.487	0.28
	(2.462)	(3.257)		(-1.171)	(-0.062)		(1.841)	(1.108)	
Asset Turnover	0.617***	0.336**	0.28	-0.250	0.179	-0.429	0.842***	0.134	0.71
	(3.371)	(1.882)		(-1.189)	(0.949)		(2.834)	(0.506)	
Idiosyncratic Volatility	0.599***	0.473***	0.13	-0.832***	-0.299	-0.533	1.407***	0.750**	0.66
	(4.659)	(3.903)		(-3.155)	(-0.994)		(4.090)	(2.032)	
Gross Margins	0.486***	0.384***	0.10	-0.232	0.314*	-0.546	0.694***	0.047	0.65
	(3.279)	(2.683)		(-1.243)	(1.564)		(2.540)	(0.178)	
Maximum Return	0.647***	0.543***	0.10	-0.349**	-0.118	-0.231	0.972***	0.638**	0.33
	(5.032)	(4.649)		(-1.658)	(-0.430)		(3.215)	(1.924)	
Financial Statement M-score	0.586***	0.524***	0.06	0.039	0.114	-0.075	0.522***	0.388**	0.13
	(3.463)	(2.908)		(0.362)	(1.211)		(2.731)	(2.326)	
Financial Health F-score	0.685***	0.387***	0.30	0.031	0.138*	-0.107	0.629***	0.226*	0.40
	(5.217)	(2.579)		(0.321)	(1.354)		(3.809)	(1.375)	
Revenue Surprise	0.603***	0.180	0.42	-0.037	-0.154	0.116	0.616***	0.310**	0.31
	(2.804)	(1.133)		(-0.226)	(-1.164)		(2.695)	(1.664)	
Accrual Volatility	0.613***	0.273**	0.34	0.087	-0.026	0.113	0.502**	0.277	0.23
	(4.365)	(2.039)		(0.442)	(-0.128)		(1.725)	(0.918)	
Illiquidity	0.560***	0.471***	0.09	-0.613**	-0.269	-0.344	1.148***	0.717*	0.43
	(4.732)	(3.696)		(-2.110)	(-0.766)		(3.199)	(1.622)	
Ch. in Forecasted Annual EPS	0.186	-0.247**	0.43	-0.313*	-0.455***	0.142	0.476**	0.187	0.29
	(1.203)	(-2.060)		(-1.556)	(-2.981)		(1.798)	(0.890)	

The table reports average benchmark-adjusted returns following high and low levels of noise, as classified based on the median level of the index .The average returns in high-and low-noise periods are estimates of a_H and a_L in the regression:

$$R_{i,t} = a_H d_{H,t} + a_L d_{L,t} + bMKT_t + cSMB_t + dHML_t + u_{i,t}$$

where $d_{H,t}$ and $d_{L,t}$ are dummy variables indicating high-and low-noise periods, and $R_{i,t}$ is the excess return in month t on either the long leg, the short leg, or the difference. Also reported are returns on a strategy that equally combines the strategies available within a given month. The sample period is from 1987:4 to 2014:12 for all anomalies beside the change in forecasted annual EPS, whose data begin 1989:1. All t-statistics shown next to the estimated coefficients are based on Newey and West (1987) heteroskedasticity and autocorrelation-consistent standard errors. ***, **, and * indicate one-tailed statistical significance at levels 1%, 5%, and 10%, respectively.

Table 4: Noise and anomalies: predictive regressions for excess returns on long-short strategies.

Anomaly	Long		Short		Long-Short	
	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat
Combination	-0.377**	(-2.322)	-0.878***	(-3.129)	0.501***	(3.237)
Beta Arbitrage	-0.292***	(-2.578)	-1.050***	(-2.623)	0.758**	(2.010)
Asset Turnover	-0.405**	(-2.050)	-0.771***	(-2.998)	0.365***	(2.383)
Idiosyncratic Volatility	-0.272***	(-2.486)	-1.135***	(-2.984)	0.863***	(2.586)
Gross Margins	-0.414**	(-1.763)	-0.863***	(-3.935)	0.449***	(3.560)
Maximum Return	-0.338***	(-2.517)	-0.976***	(-2.839)	0.638**	(2.118)
Financial Statement M-score	-0.415**	(-1.823)	-0.719***	(-3.315)	0.303***	(3.718)
Financial Health F-score	-0.392**	(-2.211)	-0.743***	(-3.375)	0.351***	(4.045)
Revenue Surprise	-0.565***	(-2.614)	-0.902***	(-2.934)	0.336***	(2.565)
Accrual Volatility	-0.372**	(-2.048)	-0.601***	(-2.895)	0.229**	(2.034)
Illiquidity	-0.281***	(-2.788)	-1.113***	(-2.695)	0.831**	(2.206)
Change in Forecasted Annual EPS	-0.445**	(-1.939)	-0.818***	(-2.891)	0.373**	(2.330)

The table reports estimates of b in the regression:

$$R_{i,t} = a + bN_{t-1} + u_t$$

$R_{i,t}$ is the excess return in month t on either the long, short or long-short self-financing anomaly portfolio, and N_{t-1} is the lagged 3-month change of noise of the index of Hu, Pan and Wang (2013). The sample period is from 1987:4 to 2014:12 for all anomalies except the change in forecasted annual EPS, whose data begin 1989:1. t statistics shown next to the estimated coefficients are based on Newey and West (1987) heteroskedasticity and autocorrelation-consistent standard errors. ***, **, and * indicate one-tailed statistical significance at levels 1%, 5%, and 10%, respectively.

Table 5: Noise and anomalies: predictive regressions for excess returns on long-short strategies controlling for FF3 factors

Anomaly	Long		Short		Long-Short	
	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat
Combination	0.121***	(2.837)	-0.225***	(-2.789)	0.346***	(3.275)
Beta Arbitrage	0.110	(1.195)	-0.394***	(-2.462)	0.504**	(2.216)
Asset Turnover	0.181***	(2.350)	-0.084	(-0.928)	0.265**	(2.022)
Idiosyncratic Volatility	0.136**	(1.755)	-0.519***	(-3.372)	0.655***	(3.214)
Gross Margins	0.025	(0.364)	-0.182*	(-1.592)	0.207*	(1.342)
Maximum Return	0.117*	(1.358)	-0.411***	(-2.924)	0.528***	(2.552)
Financial Statement M-score	-0.008	(-0.108)	-0.001	(-0.008)	-0.007	(-0.068)
Financial Health F-score	0.126**	(2.005)	-0.083**	(-1.839)	0.209***	(2.867)
Revenue Surprise	0.169*	(1.528)	-0.066	(-0.519)	0.235***	(2.603)
Accrual Volatility	0.185***	(2.759)	-0.171**	(-2.052)	0.357***	(2.684)
Illiquidity	0.115*	(1.452)	-0.507***	(-2.951)	0.623***	(2.640)
Change in Forecasted Annual EPS	0.191***	(2.690)	-0.021	(-0.187)	0.212*	(1.396)

The table reports estimates of b in the regression:

$$R_{i,t} = a + bN_{t-1} + cMKT_t + dSMB_t + eHML_t + u_t$$

$R_{i,t}$ is the excess return in month t on either the long, short or long-short self-financing anomaly portfolio, and N_{t-1} is noise variable. The sample period is from 1987:4 to 2014:12 for all anomalies except change in forecasted annual EPS, whose data begins in 1989:1. t-statistics shown next to the estimated coefficients are based on Newey and West (1987) heteroskedasticity and autocorrelation-consistent standard errors. ***, **, and * indicate one-tailed statistical significance at levels 1%, 5%, and 10%, respectively.

Table 6: Predictive regressions for excess returns on long, short and long minus short strategies controlling for Baker and Wrugler (2006) investor sentiment

Anomaly	Long				Short				Long-Short			
	N(t-1)	t-stat	S(t-1)	t-stat	N(t-1)	t-stat	S(t-1)	t-stat	N(t-1)	t-stat	S(t-1)	t-stat
Combination	-0.397***	(-2.399)	-1.764*	(-1.406)	-0.920***	(-3.238)	-3.690*	(-1.344)	0.523***	(3.405)	1.919	(1.023)
Beta Arbitrage	-0.308***	(-2.683)	-1.358*	(-1.525)	-1.127***	(-2.829)	-6.761*	(-1.547)	0.819**	(2.210)	5.396	(1.233)
Asset Turnover	-0.429**	(-2.130)	-2.099*	(-1.291)	-0.802***	(-2.984)	-2.728*	(-1.472)	0.372***	(2.361)	0.622	(0.490)
Idiosyncratic Volatility	-0.284***	(-2.559)	-1.038	(-1.144)	-1.208***	(-3.206)	-6.402*	(-1.451)	0.924***	(2.833)	5.358	(1.251)
Gross Margins	-0.451**	(-1.890)	-3.284*	(-1.535)	-0.886***	(-3.888)	-2.034	(-0.832)	0.435***	(3.484)	-1.256	(-0.853)
Maximum Return	-0.351***	(-2.572)	-1.216	(-1.213)	-1.031***	(-3.007)	-4.848*	(-1.287)	0.680**	(2.301)	3.626	(1.002)
Financial Statement M-score	-0.451**	(-1.955)	-3.123*	(-1.454)	-0.738***	(-3.343)	-1.751	(-0.944)	0.288***	(3.413)	-1.378	(-0.924)
Financial Health F-score	-0.409**	(-2.261)	-1.528	(-1.120)	-0.761***	(-3.383)	-1.543	(-0.769)	0.351***	(3.972)	0.009	(0.008)
Revenue Surprise	-0.586***	(-2.681)	-1.801	(-1.040)	-0.931***	(-2.975)	-2.569	(-1.227)	0.345***	(2.572)	0.761	(0.903)
Accrual Volatility	-0.381**	(-2.063)	-0.861	(-0.647)	-0.632***	(-2.992)	-2.710	(-0.838)	0.250**	(2.219)	1.842	(0.626)
Illiquidity	-0.292***	(-2.845)	-0.927	(-1.076)	-1.189***	(-2.896)	-6.668*	(-1.404)	0.897***	(2.422)	5.734	(1.258)
Ch. Forecasted Annual EPS	-0.467**	(-1.975)	-2.155	(-1.165)	-0.844***	(-2.937)	-2.539	(-1.149)	0.377**	(2.334)	0.375	(0.343)

The table reports estimates of b in the regression:

$$R_{i,t} = a + bN_{t-1} + cS_{t-1} + u_t$$

Ri,t is the excess return in month t on the long minus short self-financing anomaly portfolio, N_{t-1} is the noise measure at time t and S_{t-1} is the sentiment measure derived from the investor-sentiment index of Baker and Wurgler (2006). Coefficients b and c are reported in the column $N_{t-1}$and S_{t-1}, respectively. Also reported are returns on a strategy that equally combines the strategies available within a given month. The sample period is from 1987:4 to 2014:12 for all anomalies except the change in forecasted annual EPS, whose data begins in 1989:1. t-statistics are shown underneath the estimated coefficients are based on Newey and West (1987) heteroskedasticity and autocorrelation- consistent standard errors. ***, **, and * indicate one tailed statistical significance at levels 1%, 5%, and 10%, respectively.

Table 7: Predictive regressions for excess returns on long, short and long minus short strategies controlling for Baker and Wrugler (2006) investor sentiment and FF3 factors

Anomaly	Long				Short				Long-Short			
	N(t-1)	t-stat	S(t-1)	t-stat	N(t-1)	t-stat	S(t-1)	t-stat	N(t-1)	t-stat	S(t-1)	t-stat
Combination	0.119***	(2.721)	-0.147	(-0.307)	-0.231***	(-2.919)	-0.573	(-0.896)	0.351***	(3.298)	0.419	(0.456)
Beta Arbitrage	0.101	(1.088)	-0.782*	(-1.326)	-0.418***	(-2.658)	-2.056*	(-1.530)	0.519**	(2.266)	1.267	(0.783)
Asset Turnover	0.179***	(2.354)	-0.109	(-0.129)	-0.094	(-1.001)	-0.873	(-1.020)	0.274**	(2.023)	0.757	(0.578)
Idiosyncratic Volatility	0.133**	(1.668)	-0.301	(-0.562)	-0.542***	(-3.613)	-2.014*	(-1.356)	0.675***	(3.270)	1.706	(0.989)
Gross Margins	0.018	(0.268)	-0.538	(-0.741)	-0.180*	(-1.618)	0.232	(0.189)	0.198*	(1.323)	-0.777	(-0.459)
Maximum Return	0.113	(1.280)	-0.333	(-0.597)	-0.421***	(-3.009)	-0.928	(-0.784)	0.535***	(2.544)	0.589	(0.387)
Financial Statement M-score	-0.014	(-0.187)	-0.495	(-0.497)	0.004	(0.051)	0.379	(0.670)	-0.018	(-0.158)	-0.880	(-0.834)
Financial Health F-score	0.127**	(1.988)	0.141	(0.202)	-0.073**	(-1.657)	0.830**	(1.801)	0.200***	(2.700)	-0.695	(-0.875)
Revenue Surprise	0.172*	(1.506)	0.201	(0.187)	-0.072	(-0.569)	-0.508	(-0.576)	0.244***	(2.649)	0.704	(0.919)
Accrual Volatility	0.193***	(2.812)	0.626	(1.044)	-0.166**	(-2.082)	0.492	(0.368)	0.358***	(2.777)	0.128	(0.072)
Illiquidity	0.113*	(1.393)	-0.171	(-0.352)	-0.528***	(-3.062)	-1.814	(-1.182)	0.642***	(2.669)	1.637	(0.907)
Ch. Forecasted Annual EPS	0.193***	(2.735)	0.213	(0.348)	-0.021	(-0.189)	-0.045	(-0.057)	0.215*	(1.405)	0.250	(0.258)

Predictive regressions for excess returns on long, short and long minus short strategies. The table reports estimates of b in the regression:

$$R_{i,t} = a + bN_{t-1} + cS_{t-1} + dMKT_t + eSMB_t + fHML_t + u_t$$

Ri,t is the excess return in month t on the long minus short self-financing anomaly portfolio, N_{t-1} is the noise measure at time t and S_{t-1} is the sentiment measure derived from the investor-sentiment index of Baker and Wurgler (2006). Coefficients b and c are reported in the column N(t-1) and S(t-1), respectively. For sake of concision, we do not report the coefficients on the French and Fama (1993) three factors. Also reported are returns on a strategy that equally combines the strategies available within a given month. The sample period is from 1987:4 to 2014:12 for all anomalies except the change in forecasted annual EPS, whose data begins in 1989:1. t-statistics are shown underneath the estimated coefficients are based on Newey and West (1987) heteroskedasticity and autocorrelation- consistent standard errors. ***, **, and * indicate one tailed statistical significance at levels 1%, 5%, and 10%, respectively

Table 8: Predictive regressions for excess returns on long, short and long minus short strategies controlling for macroeconomic variables

The table reports estimates of b and the coefficients on the macroeconomic variables $m_{i,k}$ in the regression:

$$R_{i,t} = a_i + b_i N_{t-1} + \sum_{k=1}^{9} m_{i,k}\, Macro_{k,t-1} + d_i MKT_t + e_i SMB_t + f_i HML_t + u_{i,t}$$

where $R_{i,t}$ is the excess return in month t on either the short leg, long leg or the long minus short decile strategy of anomaly i and an equally weighted strategy of all anomalies, N_{t-1} is the noise measure at time t-1, and $Macro_{k,t-1}$ are nine lagged macroeconomic variables: recession indicator, growth in service consumption, growth in industrial production, growth in employment, growth in non-durable goods consumption, growth in durable goods consumption, the default premium, the term premium, the real interest rate, inflation, and CAY. The sample period is from 1987:4 to 2014:12 for all anomalies except the change in forecasted annual EPS, whose data begins in 1989:1. t-statistics are shown underneath the estimated coefficients are based on Newey and West (1987) heteroskedasticity and autocorrelation- consistent standard errors. ***, **, and * indicate one tailed statistical significance at levels 1%, 5%, and 10%, respectively.

Panel A: Long minus Short

	Comb.	Beta Arb.	Asset Turnover	Idiosyncratic Volatility	Gross Margins	Maximum Return	M-score	F-score	Revenue Surprise	Accrual Volatility	Illiquidity	Forecasted EPS
Ch. Noise	0.405***	0.526**	0.390***	0.672***	0.368***	0.540**	0.027	0.259***	0.274***	0.422***	0.672**	0.301***
	(3.154)	(2.002)	(2.546)	(2.689)	(2.347)	(2.228)	(0.323)	(3.013)	(2.623)	(2.899)	(2.332)	(2.712)
Consumption-Wealth Ratio	0.037	0.054	-0.046	0.103	0.095	0.050	0.152*	-0.078	-0.075	0.250**	0.055	-0.156*
	(0.433)	(0.269)	(-0.336)	(0.563)	(0.683)	(0.290)	(1.405)	(-0.942)	(-0.773)	(2.156)	(0.266)	(-1.449)
Term Premium	-0.036	-0.163	-0.575**	0.161	-0.146	0.178	-0.172	-0.274*	-0.027	-0.143	0.170	0.605***
	(-0.181)	(-0.352)	(-2.056)	(0.403)	(-0.566)	(0.481)	(-0.925)	(-1.409)	(-0.118)	(-0.524)	(0.369)	(2.553)
Real Interest Rate	-0.508	-2.147	-2.682*	0.976	-1.968*	1.021	-1.206	-0.602	0.110	-2.658**	-0.092	3.840**
	(-0.427)	(-0.714)	(-1.475)	(0.369)	(-1.286)	(0.447)	(-0.921)	(-0.486)	(0.085)	(-1.791)	(-0.030)	(2.322)
Inflation	0.043	-1.170	-0.825	0.868	-0.783	0.583	-1.170	0.675	0.442	-2.741**	0.097	4.707***
	(0.033)	(-0.367)	(-0.436)	(0.313)	(-0.483)	(0.243)	(-0.830)	(0.552)	(0.323)	(-1.828)	(0.029)	(3.115)
Default Premium	-0.528	-1.258	1.120*	-1.945**	0.618	-1.159	-1.068***	-0.323	-0.190	0.368	-1.367	-0.590
	(-1.090)	(-1.200)	(1.343)	(-1.903)	(1.050)	(-1.169)	(-2.346)	(-0.797)	(-0.425)	(0.605)	(-1.094)	(-1.161)
Recession Indicator	1.052**	0.781	0.542	2.521**	0.983	1.891*	1.528**	0.561	-0.260	1.071	2.015*	-0.085
	(1.961)	(0.568)	(0.573)	(1.978)	(1.089)	(1.536)	(1.804)	(0.939)	(-0.402)	(1.244)	(1.317)	(-0.083)
Gr. Services Consumption	-0.693*	-1.553	0.798	-1.864**	0.594	-1.758**	-0.535	-0.766	-0.345	-0.580	-0.906	-0.779
	(-1.332)	(-1.159)	(1.123)	(-1.851)	(0.841)	(-1.766)	(-0.759)	(-1.055)	(-0.555)	(-0.868)	(-0.628)	(-1.046)
Gr. Industrial Production	0.270	0.888**	-0.021	0.633*	-0.306	0.769**	-0.225	0.551**	-0.358	0.075	0.777*	0.193
	(1.079)	(1.822)	(-0.043)	(1.367)	(-0.712)	(1.783)	(-0.985)	(2.087)	(-1.265)	(0.217)	(1.473)	(0.628)
Gr. Employment	0.001**	0.001	0.001	0.004***	0.001	0.003***	0.001*	-0.000	-0.000	0.002**	0.005***	-0.001
	(2.035)	(0.919)	(0.717)	(3.558)	(0.578)	(2.782)	(1.534)	(-0.216)	(-0.175)	(1.999)	(3.670)	(-0.594)
Gr. Non-Durable Goods Cons.	0.194	-0.244	-0.044	0.370	0.526	0.465*	0.342**	-0.197	0.013	0.602**	0.347	-0.059
	(0.884)	(-0.651)	(-0.149)	(0.970)	(1.229)	(1.378)	(1.912)	(-0.978)	(0.054)	(1.720)	(0.834)	(-0.215)
Gr. Durable Goods Cons.	-0.046	-0.067	0.020	-0.134	-0.010	-0.163	0.046	-0.098*	0.037	-0.123*	-0.109	0.107*
	(-0.605)	(-0.484)	(0.214)	(-0.917)	(-0.112)	(-1.178)	(0.485)	(-1.506)	(0.519)	(-1.302)	(-0.701)	(1.302)
Obs.	329	329	329	329	329	329	329	329	329	329	329	309

Panel B: Short Leg

	Comb.	Beta Arb.	Asset Turnover	Idio. Volatility	Gross Margins	Max. Return	M-score	F-score	Revenue Surprise	Accrual Vol	Illiquidity	Forecast EPS
Noise (t-1)	-0.255***	-0.402**	-0.152*	-0.525***	-0.293***	-0.413***	-0.012	-0.101**	-0.087	-0.196**	-0.556***	-0.040
	(-2.753)	(-2.163)	(-1.622)	(-2.894)	(-2.529)	(-2.451)	(-0.238)	(-1.794)	(-1.012)	(-2.051)	(-2.619)	(-0.468)
Consumption-Wealth Ratio	-0.091*	-0.173	0.099	-0.163	-0.056	-0.116	-0.109**	-0.075*	0.017	-0.262***	-0.094	-0.056
	(-1.354)	(-1.142)	(1.034)	(-1.154)	(-0.614)	(-0.914)	(-2.114)	(-1.562)	(0.202)	(-3.005)	(-0.554)	(-0.657)
Term Premium	0.103	0.258	0.441**	-0.082	0.245*	-0.055	0.252***	0.185**	0.069	0.030	-0.068	-0.182
	(0.747)	(0.734)	(1.955)	(-0.281)	(1.370)	(-0.212)	(2.397)	(1.921)	(0.395)	(0.164)	(-0.195)	(-1.068)
Real Interest Rate	1.798**	3.480*	2.813*	0.126	3.259***	0.251	2.609***	2.359***	1.525	2.678***	0.700	-0.382
	(1.985)	(1.559)	(1.649)	(0.064)	(2.618)	(0.150)	(3.738)	(3.468)	(1.260)	(2.573)	(0.294)	(-0.327)
Inflation	1.642**	2.904	1.523	0.658	2.708**	0.976	2.537***	2.287***	1.274	3.075***	0.656	-0.973
	(1.689)	(1.170)	(0.942)	(0.312)	(2.229)	(0.554)	(3.626)	(3.457)	(1.191)	(2.884)	(0.254)	(-0.860)
Default Premium	0.596*	0.936	-0.670*	1.613**	-0.562*	0.849	0.491**	0.474**	1.164**	0.018	0.939	1.225***
	(1.496)	(1.103)	(-1.450)	(1.983)	(-1.359)	(1.128)	(1.708)	(1.885)	(2.220)	(0.049)	(0.915)	(2.680)
Recession Indicator	-1.063**	-0.671	-0.466	-2.076**	-0.859	-1.640**	-0.980***	-0.698***	-0.585	-0.807*	-1.746*	-1.113**
	(-2.218)	(-0.557)	(-0.532)	(-1.997)	(-1.259)	(-1.788)	(-2.848)	(-2.410)	(-0.804)	(-1.625)	(-1.368)	(-1.755)
Gr. Services Consumption	0.223	0.598	-0.587	1.364**	-0.823**	1.271**	-0.412	0.023	0.116	0.227	0.470	0.240
	(0.515)	(0.519)	(-1.017)	(1.681)	(-1.737)	(1.695)	(-1.193)	(0.082)	(0.245)	(0.548)	(0.383)	(0.391)
Gr. Industrial Production	-0.406**	-0.556*	-0.400	-0.529*	-0.129	-0.776***	-0.316***	-0.343***	-0.198	-0.173	-0.707*	-0.395**
	(-2.307)	(-1.432)	(-1.200)	(-1.401)	(-0.408)	(-2.433)	(-2.512)	(-2.368)	(-0.841)	(-0.763)	(-1.606)	(-2.018)
Gr. Employment	-0.000	-0.000	0.000	-0.002***	0.000	-0.001	-0.000	0.001**	0.001***	-0.002***	-0.003***	0.001*
	(-0.878)	(-0.378)	(0.572)	(-2.385)	(0.255)	(-0.818)	(-1.105)	(1.793)	(2.461)	(-3.130)	(-3.117)	(1.394)
Gr. Non-Durable Goods Cons.	-0.222*	0.113	0.186	-0.488*	-0.504*	-0.555**	-0.148**	-0.170	-0.014	-0.472**	-0.427	0.086
	(-1.414)	(0.368)	(1.038)	(-1.582)	(-1.436)	(-2.143)	(-1.733)	(-1.072)	(-0.085)	(-2.116)	(-1.225)	(0.442)
Gr. Durable Goods Cons.	0.026	0.036	-0.061	0.103	0.007	0.126	-0.047*	0.041	-0.070*	0.098*	0.077	-0.022
	(0.442)	(0.326)	(-0.943)	(0.836)	(0.097)	(1.221)	(-1.474)	(1.216)	(-1.569)	(1.401)	(0.595)	(-0.385)
Obs.	329	329	329	329	329	329	329	329	329	329	329	309

Panel C: Long Leg

	Comb.	Beta Arbitrage	Asset Turnover	Idio. Volatility	Gross Margins	Max. Return	M-score	F-score	Revenue Surprise	Accrual Volatility	Illiquidity	Forecast EPS
Noise (t-1)	0.149***	0.123	0.238***	0.147**	0.074	0.127*	0.015	0.158***	0.187**	0.226***	0.115*	0.261***
	(3.119)	(1.196)	(2.377)	(1.655)	(0.994)	(1.398)	(0.192)	(2.452)	(2.218)	(3.276)	(1.308)	(3.436)
Consumption-Wealth Ratio	-0.053*	-0.118*	0.053	-0.060	0.039	-0.066	0.044	-0.152**	-0.058	-0.012	-0.038	-0.211***
	(-1.349)	(-1.407)	(0.612)	(-0.917)	(0.466)	(-1.008)	(0.488)	(-2.264)	(-0.709)	(-0.193)	(-0.645)	(-3.729)
Term Premium	0.066	0.094	-0.134	0.079	0.098	0.122	0.079	-0.090	0.041	-0.114	0.100	0.422***
	(0.675)	(0.583)	(-0.693)	(0.544)	(0.655)	(0.878)	(0.487)	(-0.575)	(0.216)	(-0.776)	(0.717)	(3.224)
Real Interest Rate	1.368***	1.410	0.208	1.180	1.368*	1.349*	1.480*	1.835**	1.713*	0.097	0.685	3.536***
	(2.606)	(1.264)	(0.175)	(1.253)	(1.526)	(1.553)	(1.348)	(1.957)	(1.613)	(0.113)	(0.733)	(4.140)
Inflation	1.763***	1.812**	0.775	1.604**	2.003**	1.637**	1.445	3.040***	1.793*	0.413	0.831	3.813***
	(3.241)	(1.711)	(0.690)	(1.758)	(2.144)	(1.853)	(1.147)	(2.997)	(1.589)	(0.490)	(0.867)	(4.650)
Default Premium	0.067	-0.323	0.450	-0.332	0.055	-0.310	-0.577	0.151	0.974**	0.386	-0.428*	0.635***
	(0.292)	(-0.905)	(0.896)	(-1.175)	(0.152)	(-0.928)	(-1.148)	(0.458)	(2.313)	(1.039)	(-1.503)	(2.575)
Recession Indicator	-0.011	0.110	0.076	0.444*	0.124	0.251	0.547	-0.137	-0.846**	0.264	0.269	-1.198**
	(-0.037)	(0.286)	(0.101)	(1.320)	(0.202)	(0.569)	(0.626)	(-0.253)	(-1.652)	(0.504)	(0.761)	(-1.743)
Gr. Services Consumption	-0.470**	-0.955***	0.211	-0.499*	-0.229	-0.487*	-0.946*	-0.743	-0.229	-0.353	-0.435	-0.540**
	(-1.795)	(-2.548)	(0.429)	(-1.492)	(-0.451)	(-1.377)	(-1.314)	(-1.226)	(-0.483)	(-0.964)	(-1.170)	(-1.717)
Gr. Industrial Production	-0.135	0.332*	-0.420**	0.104	-0.434**	-0.007	-0.541***	0.207	-0.556***	-0.098	0.071	-0.202
	(-1.051)	(1.479)	(-1.735)	(0.637)	(-2.189)	(-0.037)	(-2.430)	(0.977)	(-2.654)	(-0.525)	(0.457)	(-0.969)
Gr. Employment	0.001**	0.001	0.001	0.002***	0.001	0.002***	0.001	0.001*	0.001*	0.001	0.001***	0.000
	(2.200)	(1.264)	(1.115)	(4.869)	(0.759)	(4.953)	(1.024)	(1.489)	(1.399)	(0.667)	(4.112)	(0.586)
Gr. Non-Durable	-0.028	-0.131	0.142	-0.118	0.022	-0.091	0.194	-0.367***	-0.001	0.131	-0.080	0.027
Goods Cons.	(-0.269)	(-0.890)	(0.762)	(-0.945)	(0.163)	(-0.696)	(1.115)	(-2.705)	(-0.005)	(0.841)	(-0.583)	(0.122)
Gr. Durable Goods Cons.	-0.020	-0.031	-0.041	-0.031	-0.003	-0.037	-0.001	-0.057	-0.032	-0.025	-0.032	0.084**
	(-0.708)	(-0.717)	(-0.806)	(-0.854)	(-0.061)	(-0.832)	(-0.012)	(-1.127)	(-0.616)	(-0.623)	(-0.874)	(1.830)
Obs.	329	329	329	329	329	329	329	329	329	329	329	309

Chapter 5. Conclusion

In the first project, I examine whether aggregate cost stickiness predicts future macro-level unemployment rate. I find that a one-standard-deviation-higher cost stickiness in recent quarters is followed by a 0.23 to 0.26-percentage-point-lower unemployment rate in the current and following quarter. In out-of-sample tests, I find significant reductions in the root-mean-squared-errors upon incorporation of cost stickiness for all models. These findings suggest that professional macro forecasters do not fully incorporate the information contained in cost stickiness.

In the second project, I investigate the impact of crude oil balance of trade on the cross-section of currency returns for 36 countries. Using classical asset pricing methodology, I find that a long/short quintile portfolio of currency sorted on oil balance of trade is priced and induces an annual risk premium ranging from 2.4 to 2.9%. I conduct the analysis using individual currencies and portfolios as test assets, both leading to the same conclusion. I also find that characteristics subsume factor beta and, hence, confirm results in the equity market (Chordia, Goyal and Shanken 2015). More interestingly, I show that the net oil balance of trade characteristic, specific to each country and varying over time, contains incremental information relative to the carry characteristic that explains currency excess returns. The fact that not only oil price but also oil net balance of trade plays a role in asset pricing is completely new to the literature.

In the third project, I explore the effect of time-varying arbitrage capital availability on the cross-section of abnormal equity returns. I investigate the relationship between arbitrage capital, proxied by a market wide-liquidity measure introduced by Hu et *al.* (2013)Hu, Pan and Wang (2013), and the future performance of a set of eleven well-known pricing anomalies. When arbitrage capital is abundant, investors are able to deploy arbitrage strategies more successfully, which leads to lower future profitability of pricing anomalies. In contrast, when arbitrage capital is scarce, investors are unable to deploy enough capital to take advantage of pricing anomalies, yielding higher profitability of the anomaly strategies subsequently. Consequently, as a priced factor, time-varying arbitrage capital helps to explain the cross-sectional returns of pricing anomalies.