A cross-sectional analysis of individual goods inflation rates *

Bingxin Xing†
ESSEC Business School

Bruno Feunou‡
Bank of Canada

Roméo Tédongap§
ESSEC Business School

May 13, 2022

Abstract

We define the individual excess inflation rate (IEIR) for a consumer good as the good's individual inflation rate (IIR) minus the general inflation rate. We document sizeable cross-sectional heterogeneity in IEIR for goods and services, which we explain by the heterogeneity in IEIR's exposure to a set of economic factors capturing common sources of variation in the prices of consumer goods. Our empirical findings, which are significant and robust, confirm our argument that goods with counter-cyclical price fluctuations have higher IEIR on average than others. Conversely, goods with pro-cyclical price fluctuations generally have lower IEIR than others. In addition, economic factors that explain the heterogeneity include pro-cyclical factors, such as long-term inflation expectations, wages, and consumer sentiment, and counter-cyclical factors, such as unemployment gap, economic policy uncertainty, and financial condition measures. These novel results contrast with the cross-sectional findings from financial assets and reveal the divergent underlying logics that lead to economic agents' different investment and consumption behaviors.

Keywords: Cross-sectional asset pricing, consumer price index (CPI), Phillips curve, factor selection, Fama-MacBeth procedure, inflation risk premium.
JEL Classification: G12, C32, C43, C55, E31, E37.

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*We benefited tremendously from discussions with Jason Allen and seminar participants at ESSEC Business School, CY Cergy Paris University, University of Nottingham. The views expressed in this paper, and all errors and omissions, are our own and are not necessarily those of the individuals or groups listed above.

†Department of Finance, ESSEC Business School, 3 Avenue Bernard Hirsch, CS 50105 CERGY, 95021 Cergy-Pontoise Cedex, France. Email: bingxin.xing@essec.edu.

‡Bank of Canada, Financial Markets Department, 234 Wellington Street, Ottawa ON K1A 0G9, Canada. Email: BFeunou@bank-banque-canada.ca. The views expressed in this paper are solely those of the authors and may differ from official Bank of Canada views. No responsibility for them should be attributed to the Bank.

§Corresponding author: Department of Finance, ESSEC Business School, 3 Avenue Bernard Hirsch, CS 50105 CERGY, 95021 Cergy-Pontoise Cedex, France. Email: tedongap@essec.edu.

1 Introduction

Financial economists have long recognized that investors care about the common factors that affect asset returns. Asset exposure to these common factors represents a measure of systematic risk in the economy, which means the type of risk that is not asset-specific and thus cannot be diversified away by forming arbitrarily large portfolios. Cross-sectional asset pricing mainly focuses on understanding how asset return sensitivities to these factors determine the expected returns required by investors to hold different assets. Explaining the cross-sectional differences in investment expected returns has produced extensive literature, with various cross-sectional pricing factors being put forward as determinants of the returns on different financial and tangible assets, such as stocks, bonds, commodities, currencies, and real estate. In rational factor asset pricing models, the discrepancy in risk premia across different assets should be linked to a corresponding dispersion of sensitivities (factor loadings, or betas) to common risk factors. In most cases, these factors capture business cycle movements well. The main findings suggest that investors demand higher returns, on average, for assets whose returns tend to move more pro-cyclically than other assets.

Like considering what assets to invest in, considering what goods and services to consume are integral to an economic agent's decision.[1] Although consumption decision-making may differ from investment decision-making, it would be reasonable to assume that economic agents are also interested in systematic factors that affect the price changes of individual consumer goods[2] and that these factors correlate with the business cycle. For example, economic agents want higher returns on their holding assets from investors' perspectives. Likewise, as consumers, economic agents hope the goods they would like to consume become cheaper, not more expensive; in the case of general

[1]If people consider buying and holding a good or service now and reselling it in the future when the price rises, it is an investment, not consumption. To distinguish between consumption and investment clearly, we assume that the goods and services in our analysis are purchased to meet consumer needs rather than pursuing returns. A good or service intended for consumption can be non-durable or durable. Because nondurables (e.g., ice cream, dental services, etc.) have short lifespans, they cannot be held long enough to be resold until prices increase. Durables (e.g., televisions, tires, etc.) may have longer lives; still, due to wear and tear and possible product upgrades on the markets, these durable goods are usually purchased to consume rather than in pursuit of profits.

[2]Throughout the paper, the term "consumer goods" or simply "goods" refers to both goods and services intended for consumption.

inflation (e.g., CPI goes up), consumers want the prices of their interested goods to rise less than others. We, therefore, measure the relative price change of a consumer good by its individual excess inflation rate (IEIR), which is defined as the good's individual inflation rate (IIR) minus the general inflation rate (e.g., CPI growth rate).[3] In contrast to asset returns, IIR is the nominal price growth rate, and IEIR is the real (or relative) price growth rate; in this sense, IIR can be seen as the nominal inflation rate for an individual good, while IEIR is the real inflation rate for the good.

To the best of our knowledge, no research has analyzed the cross-sectional differences in the expected IEIR for consumer goods and identified the potential factors that could explain this heterogeneity.[4] Figure 1 plots the sample averages of the 146 IEIR time series that we analyze in this paper, as well as their histogram. The minimum and maximum average IEIR are -18.23% and 3.36%, respectively. The figure illustrates well the considerable variation of these values in the cross-section, which is our goal in this article to explain. We regard individual economic agents primarily as consumers and examine how their consumption behavior leads to cross-sectional differences in expected IEIR across consumer goods. Our setting deviates from the large body of the literature that regards individual economic agents primarily as investors and examines how their investment behavior leads to cross-sectional differences in expected returns of investment assets.

We build on the cross-sectional asset pricing literature, but we aim to explain the cross-sectional difference in price changes of consumer goods. Our framework is inspired by arbitrage pricing theory (APT) and multifactor models, as we first postulate that a few common factors are the determinants of the IEIR for consumer goods. However, in contrast to the asset pricing literature, there is no prior theory directly relating individual goods' prices to specific common determinants for us to select factors. Hence, we rely on the economic rationale to motivate our choice. Next, we postulate a linear cross-sectional relationship between the expected IEIR of consumer goods and their sensitivities, i.e., their betas, to the common factors. We finally form the central hypothesis

[3] In a deflationary situation, the IEIR of a consumer good is the difference between the good's price decrease rate and the CPI decline rate.

[4] There are also no studies investigating the cross-sectional heterogeneity of IIR. We provide the IIR-based analysis in the online appendices.

that goods with higher IEIR beta[5] on pro-cyclical factors are associated with lower average IEIR in the cross-section. Likewise, goods with higher IEIR beta on counter-cyclical factors are associated with higher average IEIR in the cross-section.

In support of our hypothesis, if a good's IEIR beta on a pro-cyclical factor is positive, i.e., the good has a pro-cyclical price fluctuation, then the good tends to be cheaper[6] in bad times, which increases the demand for the good when consumers are worse off; this is the characteristic of inferior goods in the economics literature. Similarly, suppose a good's IEIR beta on a counter-cyclical factor is positive, i.e., the good's price fluctuates counter-cyclically, then the good tends to be cheaper in good times, prompting the demand for this good when consumers are better off, which is the characteristic of normal goods in the literature. Based on intuition, the goods that consumers pick when they are prosperous (normal goods) could provide higher satisfaction than the goods they have to choose when they are financially struggling (inferior goods) generally. We argue that consumers require lower IEIR for inferior goods than normal goods as compensation for the inconvenience they assume for demanding a good in bad economic times that they would skip in ordinary circumstances.

We explore our cross-sectional predictions using 146 categories of goods and services whose price indexes cover January 1990 to December 2019. The paper's main results relate to the cross-sectional valuation of six benchmark factors, including three pro-cyclical and three counter-cyclical factors. These factors are chosen based on economic arguments and the extant literature on the main drivers of the inflation dynamics. The three pro-cyclical factors include two macroeconomic, i.e., long-term inflation expectations and wages, and one behavioral, i.e., the consumer sentiment. Likewise, the three counter-cyclical factors include two macroeconomic, i.e., the unemployment gap and the economic policy uncertainty, and one financial, i.e., the national financial conditions index. The empirical methodology encompasses basket sorts on individual good betas on these factors as

[5] A consumer good's IEIR beta on a factor represents the time-series covariance between the good and the factor.

[6] The IEIR-based analysis is on real (or relative) price changes, so cheaper or more expensive in this paper describes the relative price increases or decreases (relative to the CPI changes), separately. The IIR-based study is on the nominal (or absolute) price changes of the good itself, available in the appendices on the authors' websites.

well as cross-sectional regressions of Fama and MacBeth (1973) to estimate the factor lambdas. Our main finding is that our six benchmark factors are highly significant and robust in explaining the cross-sectional heterogeneity of consumer goods inflation rates.

The basket sorts suggest that a consumption strategy that focuses only on the inferior goods rather than the normal goods generates a significant purchasing power gain that averages between 0.11% and 0.69% per annum. Moreover, if basket sorts are relative to betas on a counter-cyclical factor, this gain is between 0.31% and 0.69% per annum. Otherwise, it ranges between 0.11% and 0.40% per annum. Across individual consumer goods, we see a wide dispersion in their IEIR sensitivities to the common factors, which generates cross-sectional variation in the average IEIR attributed to them. Likewise, the estimated factor lambdas are highly statistically significant overall, and their signs are all consistent with the theory, i.e., pro-cyclical factors have a negative lambda. In contrast, counter-cyclical factors have a positive lambda.

We analyze the ability of our benchmark factors as joint determinants of individual consumer goods prices. We document that their explanatory power, as measured by the time series of adjusted R^2 (R^2_{adj}), is higher during the period corresponding to the four rounds of quantitative easing (QE) launched by the Fed to fight the financial crisis. They lasted from December 2008 to October 2014. Over the QE period, our benchmark factors explain time-series variations in individual goods inflation rates with a median R^2_{adj} between 40% and 55% across consumer goods. This median explanatory power does not exceed 22% in non-QE periods. This observation is striking as the QE policy directly impacts financial conditions such as interest rates, inflation, unemployment, and wages, reinforcing their effects with substantial implications for the consumer sector.

We complete our empirical investigation by showing that our central hypothesis is validated if we consider various multi-factor models combining our benchmark and single-factor models with fourteen additional factors, including eight pro-cyclical and six counter-cyclical factors. Likewise, our results are robust to betas estimated from the alternative rolling window. Additional findings suggest that the changes in the cross-sectional distribution of IEIR betas represent valuable information for explaining time-series variation in the general inflation risk premium.

This paper is somewhat related to the immense literature on the inflation risk premium and its determinants. Numerous contributions in the literature (see, e.g., Bekaert and Wang; 2010 for an excellent survey) aim at providing time series reduced-form and structural models which decompose nominal bond yields into three economically essential components, including the inflation risk premium. Most of the recent economic questions center around the economic drivers of the inflation risk premium, mainly whether models can rationalize a negative inflation risk premium. Regardless of the question, the object of interest is always the time series properties of CPI's growth rate. We instead analyze price changes in individual goods and inquire whether differences in expected inflation across goods are related to differences in their exposures to some well-known aggregate macroeconomic factors. Our paper thus can be conceived as a cross-sectional analysis of the inflation risk premium.

The general inflation rate (e.g., CPI) might be challenging to assess for a typical household. In addition, the prevailing inflation rate includes categories of goods that a particular household may not consider. In this sense, individual goods inflation rates could be more meaningful to households because they provide the price change information on disaggregated categories of goods and services, which are more practical and flexible references for real-world households with different consumption habits.

Very few papers have investigated the disaggregated prices dynamic in the extant literature. Even when such a study exists, the focus is mainly on two categories of goods: durable and nondurable goods. Eraker et al. (2015) provide a recent contribution, where they show that, relative to nondurable goods, the predictability of real growth rate is significantly higher using durable goods inflation. This result implies that the equity returns of durable goods-producing firms have a more considerable negative exposure to expected inflation risks. Our focus is different, we do not only investigate a large cross-section of goods (146), but more importantly, we are interested in observed macro factors that can explain the cross-sectional heterogeneity of inflation.

Perhaps the papers that are closely related to ours are the contributions by Reis and Watson (2010) and Luciani (2020) where dynamic factor models are used to disentangle changes in prices due to common shocks from changes due to idiosyncratic shocks. While, in spirit, our paper does a similar decomposition, our contribution is distinct in three critical dimensions. First, we focus on a set of observed common sources of variation in prices, not latent ones. Next, our technique is different given the question investigated, i.e., we rely on the cross-sectional asset pricing method of Fama and MacBeth (1973) instead of the factor analysis of Stock and Watson (2005). Finally, and most importantly, the interest in the two previous papers is on the Phillips curve. We aim to gauge how exposures to a selected set of observed economic factors can rationalize the observed difference in inflation rates among consumer goods.

Our paper is also distinct from a growing literature studying the determinants of the cross-sectional heterogeneity in reported inflation expectations. Malmendier and Nagel (2015) is one of the most noticeable contributions. They show that differences in people forecasting experiences are strongly associated with differences in forecasts. Our focus is different as we seek to predict differences in observed consumer good prices using differences in exposures to economic factors. From a slightly different angle, Reis (2021) establishes that the discrepancy between long-run market and survey-based inflation expectations has large business-cycle fluctuations. He also shows that it is systematically correlated with monetary policies and is driven mainly by disagreement, both between households and traders and between different traders. Gorodnichenko and Weber (2016) study the cross-section of the volatility of stock market returns across firms with more or less sticky prices. Their findings suggest that, after monetary policy announcements, the conditional volatility of stock market returns rises more for firms with stickier prices than firms with more flexible prices. Boivin et al. (2009) is probably one of the most influential contributions which examine the cross-section of consumer goods prices. The main finding is that disaggregated prices appear sticky in response to macroeconomic and monetary disturbances but flexible to sector-specific shocks. The price stickiness is the central focus of that literature, which is far from our primary interest.

The rest of the article breaks up as follows. In Section 2, we define our setup and discuss the theoretical intuition, discuss testable hypotheses, and present the empirical methodology with a discussion on factor selection. In Section 3 we introduce the data, report and interpret the relevant descriptive statistics. Section 4 contains a thorough empirical assessment of the proposed theory with additional findings. Section 5 concludes. A supplemental appendix available from the authors' web pages contains additional material, including further analyses and robustness checks, and opposite findings on stock returns.

2 Theoretical intuition and empirical methodology

2.1 The individual excess inflation rate of a consumer good

To study the cross-sectional differences in average price changes among individual consumer goods, we start by quantifying the variable of interest, which we refer to as the individual excess inflation rate (IEIR) throughout the article, by analogy to the real return of an asset. Investors care about real asset returns, which they use to analyze their investment performance. Similarly, consumers care about how individual good prices grow versus the general price level in the economy. We, therefore, propose to analyze the performance of an individual consumer good through its IEIR, i.e., by the difference between the change in the log good price and the change in the log general price level.

As investors, rational economic agents want higher returns on their investment assets. From a consumer's perspective, rational agents would like the goods they want to consume to become cheaper, not more expensive.[7] However, what does "cheaper" or "more expensive" mean through time? Plain thinking connects "cheaper" with "lower price" and "more expensive" with "higher price", respectively. If the hourly cost of a service S increases from \$11 in 1970 to \$50 in 2020, it has become more expensive by \$39 in absolute terms, i.e., nominal terms. Now, consider how

[7] In economic theory, goods generally have downward-sloping demand curves, which means that lower price leads to higher demand and stimulates higher consumption. Since higher consumption brings higher utility, rational agents as consumers would prefer goods to become cheaper rather than more expensive.

the general price level has evolved over the same period. The general price level, as measured, for example, by the consumer price index, CPI, was around 39 in 1970 and 259 in 2020.[8] The main thrust of general economic theory is that rational individuals measure their motives in "real" terms (i.e., in units of goods), not in "nominal" terms, i.e., values expressed in money (see Arrow; 1980). For example, in real terms, the hourly cost of the service S decreases from 0.282 (i.e., $\frac{11}{39}$) units to 0.193 (i.e., $\frac{50}{259}$) units, so it has become cheaper by 0.089 units over the period. Most articles in the cross-sectional asset pricing literature also analyze asset excess returns in real rather than nominal terms. This observation further inspires us to measure and analyze the IEIR of a good, i.e., whether it becomes cheaper or more expensive, in real terms. The IEIR of a good measures the growth rate of its price in real terms. It represents the consumer's purchasing power evolution over a particular good.

Formally, consider an economy with N goods denoted by $i = 1, 2, \ldots, N$, and let $P_{i,t}$ be the price of good i at date t. Without loss of generality, assume the existence of a price index whose value at date t is denoted by $P_{0,t}$, which tracks through time the value of a representative basket of the N goods. While changes in the log price index measure the growth rate of the general price level in the economy, i.e., the standard inflation rate, prices of the different goods may have quite heterogeneous growth rates. Let $\pi_{0,t}$ and $\pi_{i,t}$ denote the general inflation rate and the individual inflation rate (IIR) of good i. By definition, we have

$$\pi_{i,t} \equiv \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \quad \text{for} \quad i = 0, 1, 2, \ldots, N. \tag{1}$$

Likewise, we define the IEIR of good i as follows:

$$\pi^e_{i,t} \equiv \ln\left(\frac{P_{i,t}/P_{0,t}}{P_{i,t-1}/P_{0,t-1}}\right) = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) - \ln\left(\frac{P_{0,t}}{P_{0,t-1}}\right) = \pi_{i,t} - \pi_{0,t}, \quad \text{for} \quad i = 1, 2, ..., N. \tag{2}$$

Compared with the definition of the return for an investment asset, the IIR for a consumer good,

[8] https://www.minneapolisfed.org/about-us/monetary-policy/inflation-calculator/consumer-price-index-1913-

$\pi_{i,t}$, as shown in Equation (1), is the nominal price growth rate, while the IEIR of the good, $\pi^e_{i,t}$, as defined in Equation (2), is the real (or relative) price growth rate; in this sense, IIR is the nominal inflation rate for an individual good, while IEIR is the real inflation rate for the good.

2.2 Consumer goods versus investment assets: testable hypothesis

From an investor's viewpoint, if an asset tends to have a lower return in hard times when the investor is worse off, i.e., the asset return is pro-cyclical, a rational risk-averse investor would require a higher expected return to investing in such an asset. Hard times may correspond to low revenue or income periods, such as wage and salary, or periods with high unemployment rates. In contrast, an asset with a counter-cyclical return can be considered a hedge; such an asset can prevent the investor's situation from getting worse in hard times. Therefore, an investor would generally tolerate a lower expected return for holding such an asset. Investors have to make a tradeoff between expected return and risk, where risk here is a measure of the pro-cyclicality of the asset return. The risk-return tradeoff builds the cornerstone of the modern asset pricing theory.

We want to translate this theoretical intuition from asset valuation to consumer goods. We ask ourselves the following question: from a consumer's point of view, is there a theoretically sound relationship between the expected IEIR of a consumer good and a measure of pro-cyclicality of the IEIR? If any, what is the sign of this relationship?

Contrary to investment assets, goods or services intended for consumption do not have the typical characteristic of buy-low-sell-high for pursuing higher rewards as investment assets, nor can consumers extract hedging benefits from purchasing them. Therefore, goods whose IEIR are pro-cyclical (goods that tend to be cheaper or more affordable in bad economic times) are not necessarily more attractive to consumers for the same reason hedge assets would be for investors. Moreover, there is no such thing as the risk-return tradeoff for consumer goods. Therefore, consumers have no motives to tolerate a higher IEIR for goods with pro-cyclical price changes. We argue the opposite, and our reasoning is as follows.

Consumer revenues such as wages and salaries generally drop during bad times such as economic recessions. Constrained by reduced budgets, consumers have to increase their demand for relatively cheaper goods, i.e., goods with lower IEIR than others, in difficult times. These goods with pro-cyclical IEIR can typically be considered inferior goods, i.e., goods whose demand increases in challenging times because they are more affordable and are not necessarily those consumers usually prefer. So, in general, i.e., when the economy recovers from recessions, consumer demand for such goods will decrease, leading to a lower required equilibrium price; thus, the expected IEIR for inferior goods will be lower than others. By contrast, goods with counter-cyclical IEIR can naturally be eligible as normal goods, i.e., goods whose demand decreases in hard times because of tight budgets and would be preferred by consumers otherwise. So, in ordinary circumstances, i.e., on average, consumption willingness on normal goods will be stronger than in bad times, resulting in higher expected equilibrium prices, thus, higher expected IEIR.

Figure 2 helps illustrate the mechanism, presenting the impact of a recession on normal goods (left panel) and inferior goods (right panel). When a recession hits, consumers' income generally declines. Therefore, consumers have to reduce the consumption of normal goods and replace them with inferior goods, which shifts the demand curve for normal goods to the left and inferior goods to the right (①), from D_0 to D_1. It then prompts producers to supply less normal goods and more inferior goods, shifting the supply curve for normal goods to the left and inferior goods to the right (①'), from S_0 to S_1. These two shifts (① and ①') lead to lower consumption and higher price for normal goods in the new equilibrium (point 1) than the original (point 0). It is the opposite for inferior goods, i.e., higher consumption and lower price in recessions.

When the recession ends and the economy is recovering to ordinary circumstances, before the supply curve S_1 moves, consumers expect higher revenues, which means they will be able to afford more of the goods they prefer in general. The increasing (decreasing) consumption willingness on normal (inferior) goods will shift the demand curve to the right (left), from D_1 to D_2, as shown by the dashed line shift (②); this will drive the expected consumption up (down) from q_1 to q_2, and the expected price up (down) from p_1 to p_2 in the final equilibrium (point 2), which implies a higher (lower) expected IEIR for normal (inferior) goods. As the economy returns, the supply curve will then respond to the demand curve shift.

From the above reasoning and intuition, we form the testable hypothesis that the expected IEIR is lower (higher) for goods whose IEIR fluctuates pro-cyclically (counter-cyclically). More formally, let f_t be a pro-cyclical factor, i.e., a variable that covariates positively with the gross domestic product (GDP). If $\text{cov}\left(\pi^e_{i,t}, f_t\right) > 0$ (or $\beta > 0$), then good i tends to be cheaper in recessions. We hypothesize that the higher the covariance (or β) with the pro-cyclical factor, the lower the expected IEIR, $\mathbb{E}\left[\pi^e_{i,t}\right]$, required by consumers to compensate for the inconvenience or constraint they face for having to consume such goods in hard times. In the cross-section of consumer goods, there should be a negative relationship between the time-series average of IEIR (i.e., the expected IEIR, $\mathbb{E}\left[\pi^e_{i,t}\right]$) and its covariance (or β) with a pro-cyclical factor. Conversely, the relationship should be positive if the factor is counter-cyclical. This rational intuition is opposite to the one that holds for the cross-sectional relationship between expected asset returns and their exposure (i.e., covariance or β) to business cycle variables as widely studied in the asset pricing literature.

2.3 Empirical methodology

To empirically assess the relationship between the expected IEIR of consumer goods and their comovement with business cycle fluctuations, we rely on the two-pass cross-sectional regression method of Fama and MacBeth (1973). This approach is popular for evaluating linear factor models in asset pricing. This methodological choice is motivated by the analogy between the return of an asset from an investor's perspective and the IEIR of a good from a consumer's perspective.

Formally, we assume that there are K business cycle variables which are the main factors consumers care about when making their consumption decisions, denoted by $j = 1, 2, \ldots, K$, and let $f_{j,t}$ be the realization of the factor j at date t. We assume that the relative price changes of consumer goods are related to the factors through the following linear factor time series model:

$$\pi_i^e = \alpha_i + \beta_{i,1} f_1 + \beta_{i,2} f_2 + \ldots + \beta_{i,K} f_K + \epsilon_i \tag{3}$$

where π_i^e is the IEIR of the consumer good i, f_j is the value of the factor j, and ϵ_i is the idiosyncratic component of the IEIR of the consumer good, i.e., the component uncorrelated to business cycle fluctuations. Given the time series data on prices for the different categories of consumer goods and the consumer price index, we measure the IEIR of these consumer goods as defined in equation (2). Together with the time-series data on the business cycle variables, equation (3) can be estimated using ordinary least squared time series regressions in the first pass to obtain the exposures of consumer goods to business cycle fluctuations, i.e., the $\beta_{i,j}, \quad i = 1, 2, \ldots, N, \quad j = 1, 2, \ldots, K$.

We further postulate the following linear cross-sectional relationship between the expected IEIR of consumer goods and their exposure to business cycle fluctuations as measured by the betas estimated in the first pass:

$$\mathbb{E}\left[\pi_i^e\right] = \lambda_0 + \lambda_1 \beta_{i,1} + \lambda_2 \beta_{i,2} + \ldots + \lambda_K \beta_{i,K}, \tag{4}$$

where the coefficients $\lambda_j, \quad j = 1, 2, \ldots, K$ measure the sensitivities of the expected IEIR of consumer goods to their loadings on business cycle fluctuations. These coefficients can be estimated using ordinary least squared cross-sectional regressions in the second pass. Cochrane (2005a, Section 12.3) discusses in detail the Fama-MacBeth procedure for running cross-sectional regressions and for producing standard errors and test statistics. Given our previous discussion, we expect $\lambda_j < 0$ if the factor j is pro-cyclical and $\lambda_j > 0$ if the factor j is counter-cyclical.

2.4 Factor selection

To the best of our knowledge, this is the first study that examines the explanations for the heterogeneity in relative price changes among different goods and services. We rely on their covariation with observed economic factors. However, the ultimate difficulty is a lack of theoretical guidance for factors selection, like asset pricing theories that guide the choice of factors that are determinants for asset returns. These latter theories encompass the capital asset pricing model (CAPM), the consumption-based CAPM, the production-based CAPM, the intertemporal CAPM, models with frictions such as transaction costs, or models with reference-dependent preferences, such as disappointment aversion, to name a few.

Our variable of interest, i.e., the IEIR of a consumer good as defined in equation (2) is essentially inflation-based, so in principle, we should select factors that capture common sources of variation in the prices of goods. Inspired by arbitrage pricing theory (APT) and cross-sectional multifactor models, we postulate that a few common factors are the determinants of IEIR of consumer goods, and we rely on the economic rationale to motivate our choices for the factors. We further examine the robustness of our findings to other potential factors.

Research on inflation dynamics has a long history in economics, dating back to Friedman et al. (1968) who presented a theory that relates the short-run behavior of inflation π_t to the expected inflation z_t and the gap between unemployment and its natural rate $u_t - u_t^*$. Milton Friedman's Phillips curve can be expressed as

$$\pi_t = z_t + \beta(u_t - u_t^*) + \epsilon_t. \tag{5}$$

Since Friedman's work, his model has been a workhorse of macroeconomics for decades. Researchers have refined the model extensively. We start from the conventional Phillips curve model and closely follow Blanchard et al. (2015) – a paper that nicely summarizes a vast empirical literature on inflation dynamics. Formally, our baseline specification for equation (3) writes as an "augmented" Phillips curve model for an individual consumer good as follows:

$$\pi_i^e = \alpha_i + \beta_{i,\pi}\left(\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*\right) + \beta_{i,u}\left(u_t - u_t^*\right) + \beta_{i,w}w_t + \beta_{i,s}s_t + \beta_{i,pu}pu_t + \beta_{i,fc}fc_t + \epsilon_{i,t}. \tag{6}$$

The first factor measures the difference between long-term inflation expectations, $\pi_t^{(\mathrm{LTE})}$, and the average inflation over the previous twelve months, $\pi^*_{0,t-1}$. Long-term inflation expectations approximate the importance of some firms setting prices in a rather forward-looking way. Lagged average inflation captures the role of "intrinsic persistence" or different forms of inertia in the price-setting process that could precipitate upward or downward drift in the aggregate inflation rate. The second factor is linked to variations in the labor market slack – as measured by the unemployment gap $u_t - u_t^*$, where u_t is the civilian unemployment rate and u_t^* is the natural rate of unemployment. Most of the recent literature has concentrated on the stability over time of the parameters β_π and β_u, and explains the evolution of average inflation. In this paper, we depart from the existing literature on inflation time-series dynamics and explore the effects of these variables on the cross-sectional heterogeneity of IEIR among consumer goods.

The first two factors drive the Phillips curve. Our baseline model specification (6) is an "augmented" Phillips curve for an individual consumer good as it also incorporates wage and salary disbursements (w_t), consumer sentiment (s_t), economic policy uncertainty (pu_t), and financial conditions (fc_t) as additional factors. In the context of cross-sectional analysis, we think that wage and salary disbursements may be a potential source of common variation in prices. A rise in wages can push up the cost of goods and services due to the income effect on the shift of the demand curve. Consumer sentiment may also affect consumer goods prices. If people are confident about the future, they will likely shop more. In contrast, when consumers are uncertain about what lies ahead, they tend to save money and make fewer discretionary purchases. Negative sentiment weakens demand for goods, thus their prices. Economic policy uncertainty is another potential factor. The Fed uses its main policy instrument, the target rate, to stimulate the economy or discourage excessive spending when inflation gets out of control. Finally, recent research by Del Negro et al. (2015), Christiano et al. (2015), Christiano et al. (2014) and Gilchrist et al. (2017) suggests that changes in firms' financial conditions also help to explain inflation dynamics. López-Salido and Loria (2020) document that in the United States and the Euro zone, tight financial conditions carry substantial downside inflation risks. We study the cross-sectional implications of firms' financial conditions by inquiring whether the difference in inflation between two goods is related to those goods' covariation with financial conditions.

The following section discusses the data on consumer goods prices and the factors used to build the variable of interest, IEIR, and actual regressors. Next, we present relevant summary statistics on these variables and discuss factors' cyclicality. Also, we empirically examine our central hypothesis that consumer goods' IEIR loadings on pro-cyclical factors are negatively related to the average IEIR in the cross-section. However, it is the opposite for counter-cyclical factors.

3 Data and descriptive statistics

3.1 Data

We obtain the individual price indices for 146 categories of goods and services, $P_{i,t}$, $i = 1, 2, ..., 146$, from the U.S. Bureau of Labor Statistics (BLS)[9]. Table 1 displays the 146 categories of goods and services included in our study. They belong to several classes: foods, energy, core services (market-based and non-market-based) classes, and core goods and cover the general aspects of consumers' lives. Luciani (2020) provides a detailed description of the consumer goods prices data. These goods include nondurables, durables and services, and we assume they are primarily purchased for consumption rather than any other purpose. The dataset used for our empirical investigation is an unbalanced panel comprising 360 months (30 years), from January 1990 to December 2019. Indeed, some of the individual price indices are available from January 1947. The choice of the starting date reflects our desire to maximize the sample length while considering as large as possible the number of individual price index series available every month. We arrive at a minimum number of available price indices per month of 56 in our sample. We use the price data to construct the

[9] According to the terminology adopted in the literature of disaggregate price study, as in Domberger (1987) and Lach and Tsiddon (1992), among others, each of the 146 price indices, compared to the aggregated price index representative, e.g., CPI, is the sub-aggregated representative for the corresponding category, so this analysis belongs to an inter-market rather than intra-market study; then, inferior goods and normal goods in this paper are cross-category substitutes in economic cycles.

dependent variable, i.e., the IEIR.

We use the consumer price index (CPI) as the measure for the general price level in the economy, $P_{0,t}$, which tracks the value of a given basket that includes, among others, some representatives of the 146 categories of goods through time. The data available from the BLS is the CPI for All Urban Consumers: All Items in the U.S. City Average. It measures the average monthly change in the price for goods and services paid by urban consumers between any two time periods. It can also represent the buying habits of urban consumers. This index includes roughly 88% of the total population, accounting for wage earners, clerical workers, technical workers, self-employed, short-term workers, unemployed, retirees, and those not in the labor force. Our inflation rate and the IEIR of an individual consumer good are the year-on-year growth rate of the CPI and the respective consumer good price, respectively.

Unless otherwise specified, all remaining data for our study come from the Federal Reserve Economic Data (FRED) online database. We use these data to construct the economic factors capturing common sources of variation in the price changes of consumer goods. Long-term inflation expectations, $\pi_t^{(\mathrm{LTE})}$, are data on the 10-year expected inflation. The Federal Reserve Bank of Cleveland estimates the expected rate of inflation over the next 30 years along with the inflation risk premium, the real risk premium, and the real interest rate. Their estimates are calculated with a model that uses Treasury yields, inflation data, inflation swaps, and survey-based measures of inflation expectations. The reported numbers are annualized, e.g., 1.5% for the 10-year inflation expectation means that inflation is expected to average 1.5% per year over the next ten years. The average inflation over the previous 12 months, $\pi^*_{0,t-1}$, is constructed as follows:

$$\pi^*_{0,t-1} = \frac{1}{12}\sum_{j=1}^{12} \pi_{0,t-j}. \tag{7}$$

To construct the unemployment gap, $u_t - u_t^*$, we take the difference between the unemployment rate and the noncyclical unemployment rate. The unemployment rate represents the number of unemployed as a percentage of the labor force. Labor force data are restricted to people 16 years of age and older who reside in one of the 50 states or the District of Columbia. They do not live in institutions (e.g., penal and mental facilities, homes for the aged) and are not on active duty in the Armed Forces.

For wages, we use data on the compensation of employees received: wage and salary disbursements, which we convert into per capita data by dividing by the population. The factor w_t represents the year-on-year growth rate of the per capita series. The consumer sentiment factor is constructed from the University of Michigan's Consumer Sentiment data. The Michigan Consumer Sentiment Index (MCSI) is a monthly survey of consumer confidence levels in the United States conducted by the University of Michigan. The survey is based on telephone interviews that gather information on consumer expectations for the economy. The factor s_t is the year-on-year growth rate of the MCSI series. The economic policy uncertainty factor is built from data on the Economic Policy Uncertainty Index (EPUI) for the United States. The factor pu_t represents the year-on-year growth rate of the EPUI series. The financial condition factor derives from the Chicago Fed's National Financial Conditions Index (NFCI) data, as a proxy that provides a comprehensive weekly update on U.S. financial conditions in money markets, debt and equity markets, and the traditional and "shadow" banking systems. Positive values of the NFCI indicate financial conditions that are tighter than average, while negative values indicate financial conditions that are looser than average. The factor fc_t represents the monthly average of the weekly NFCI values.

The variables used to construct our six benchmark factors of equation (6) are listed and further described in the upper panel of Table 2. The lower panel lists data descriptions for fourteen additional variables used to construct other potential factors to verify the robustness of our empirical findings. Finally, the GDP growth rate is computed from the real gross domestic product per capita, as the change in the log value from one quarter to the next, then annualized by multiplying by 4. In what follows, we present the relevant descriptive statistics of the data.

3.2 Descriptive statistics

In Table 1, the 146 goods and services are listed in descending order of their IEIR, including 61 positive and 85 negative categories, and the maximum value is 3.36%, while the minimum is −18.23%, which is also reflected on the left panel of figure 1. In addition, as IEIR goes from high to low, the corresponding category gradually shifts from services and nondurables to durables, implying that price settings for services and nondurables appear to be more flexible or forward-looking than durables, and generally lead the inflation. In contrast, prices of durable goods reveal greater stickiness and, on average, lag behind the general inflation.

To further illustrate the cross-sectional difference, Table 3 presents the time series descriptive statistics of the cross-sectional mean, standard deviation, skewness, excess kurtosis, and percentiles of the 146 IEIR series. A typical good price grows annually 0.50% less than the inflation rate. The average annual dispersion of 5.31% around the typical IEIR indicates the considerable heterogeneity among IEIR of goods over time. To further illustrate this heterogeneity, we compare the discrepancy between the 5th and the 95th percentiles of the 146 IEIR. The 5th percentile averages −7.86% while the 95th percentile averages 6.28% through time, a difference of 14.14%. Notice that these 5th and 95th percentiles are very large compared to the median IEIR that averages −0.24% through time, illustrating that an IEIR of a consumer good is likely to be more extreme than normal, and this is confirmed by the large IEIR cross-sectional excess kurtosis that averages 9.24 through time. The negative IEIR cross-sectional skewness, averaging −0.42 through time, is in line with the fact that, on average, the cross-sectional mean is less than the cross-sectional median of the IEIR. It is consistent with the feature shown by the right panel of the figure 1: the fitted probability density function (pdf) demonstrates spiked left-skewed distribution.

In Figure 3, we plot the time series patterns of the cross-sectional moments of the IEIR and highlight the NBER recessions. These cross-sectional moments show substantial time-series variations, as confirmed by their descriptive statistics in Table 3. We observe that something is going on during recessions. In particular, the cross-sectional mean and median of IEIR tend to peak around recessions. Their time series correlation with real GDP growth rate are -0.19 and -0.18, respectively, as displayed in Table 3. There was a substantial surge during the 2008 financial crisis, followed by a solid downward correction in late 2009. It shows a similar but relatively mild "jump-and-recover" pattern during the eight-month economic downturn in 2001. Likewise, the cross-sectional standard deviation of IEIR tends to peak around recessions, and it has a correlation of -0.31 with the real GDP growth rate. It shows a sharp rise in price dispersion during the 2008 financial crisis, which peaked around June 2009, then fell back rapidly to nearly pre-recession levels at the end of 2009. The pattern of the cross-sectional skewness shows that asymmetry in IEIR decreased significantly during the 2008 financial crisis and grew back from the mid-2009 economic recovery. Cross-sectional skewness changed signs less frequently than before the 2008 crisis and has been primarily negative since then, implying a higher likelihood that a few consumer goods will experience a sharp drop in their prices. The cross-sectional kurtosis increased significantly during the 2008 financial crisis and fell back from the mid-2009 economic recovery.

Recall that our testable hypothesis involves the cyclicality of the factors driving the IEIR of consumer goods. We measure the cyclicality of a given factor by its correlation with the real GDP growth rate. In Table 4, Panel A reports the descriptive statistics of the six benchmark factors, their correlations with the real per capita GDP growth rate and their implied cyclicality. The three factors, $\pi_t^{(\mathrm{LTE})} - \pi^*_{0,t-1}$, w_t and s_t are pro-cyclical factors with correlations of 0.43, 0.34, and 0.40, respectively, with GDP growth rate. The other three factors, $u_t - u_t^*$, pu_t and fc_t are counter-cyclical factors with correlations of -0.17, -0.35 and -0.60, respectively, with GDP growth. Also, pro-cyclical factors are negatively skewed while counter-cyclical factors are positively skewed. Moreover, the first-order autocorrelation coefficients for five factors are very high, which implies that those factors are predictable by their past values. Panel B of Table 4 displays the correlations between the six benchmark factors, which shows that, in general, pro-cyclical factors are negatively correlated with counter-cyclical factors.

Since economic agents are primarily concerned with deviations from their predictions about economic variables, the actual factors should be considered the innovations in the original variables. For this, we work with factor innovations in equation (6) instead of the original factors. We measure factor innovations by the residuals from univariate ARMA(1,1) models estimated on the original factors. Working with factor innovations also avoids potential econometric issues in time series regressions on very persistent factors. The descriptive statistics of the final factors are presented in Panel A of Table 5. The sample means, medians, and AR(1) coefficients are close to zero, and the factors' cyclicality remains unchanged. In Panel B, the residuals of pro-cyclical factors are negatively correlated with those of counter-cyclical factors, and final factor correlations are much lower overall than original factor correlations. In our subsequent empirical investigation, the actual factors represent factor innovations rather than the original ones.

4 Empirical estimation and robustness checks

4.1 Basket sorts

Before we get to the estimation and the analysis of our primary empirical model described by equations (3) and (4), let us give a flavor of our results. We conduct a simple illustrative exercise popularly used in the cross-sectional asset pricing literature. First, we sort individual consumer goods based on the univariate beta of their IEIR on each of the benchmark factors of equation (6). Then, we form two baskets of goods based on the median of each factor loading and examine whether the average IEIR of these baskets displays a pattern that is consistent with the economic intuition discussed in Section 2.2. Our methodology closely follows the work of Ang et al. (2006) in portfolio sorts for investment assets.

For every month $t \geq h$ throughout the whole sample period, we calculate conditional realized betas from the univariate time series regression of the IEIR on each of the factors in equation (6), using h months of data from month $t-h+1$ to month t. We also calculate the conditional average monthly IEIR over the same h-month period for each consumer good. The beta and the IEIR are thus measured contemporaneously. Goods are further allocated into two median baskets based on whether their realized beta is below or above the median beta. The IEIR of these median baskets are calculated by averaging across goods. Finally, we take the time-series average of the basket IEIR and the IEIR difference between the high (H) and the low (L) basket. As argued by Ang et al. (2006), the use of overlapping information in estimating the conditional betas is more efficient but induces moving average effects, which can be accounted for by reporting robust standard errors that are adjusted following Newey and West (1987).

Let's start our discussion with Panel A of Table 6. It displays annualized average IEIR and IEIR differences for the two baskets formed by sorting consumer goods based on their univariate realized betas on actual benchmark factors. This panel estimates conditional betas every month with a rolling window of $h = 60$ months. Interestingly, the beta sign is different for the low versus the high basket, nicely reducing our analysis to the inferior goods versus normal goods interpretation of Section 2.2. From this observation, we point out that, in absolute value, the IEIR spread is interpretable as the purchasing power gain on a consumption strategy that focuses only on the inferior goods rather than the normal goods.

For basket sorts on the betas on pro-cyclical factors, the low basket is interpretable as the normal goods, and the high basket would correspond to the inferior goods. Subpanels **f1**, **f3** and **f4** display results for sorting on betas on our three pro-cyclical benchmark factors. Overall, the low basket has an average IEIR higher than the high basket, corroborating our intuition that normal goods prices grow more than inferior goods prices on average. In particular, sorting on the wages beta leads to a low (high) basket IEIR of -0.32% (-0.64%) per annum, and the spread in average IEIR between the high and the low baskets is -0.33% per annum. Similarly, we find that goods with higher covariance with consumer sentiment have lower IEIR overall. On average, prices of goods with the low (high) beta on consumer sentiment grow 0.42% (0.53%) less than the CPI per annum. As a result, the average IEIR difference between the high and low baskets is -0.11% per annum.

We now discuss the basket sorts on the betas on counter-cyclical factors. Here the low basket is now interpretable as the inferior goods while the high basket would correspond to the normal goods. Subpanels **f2**, **f5** and **f6** display results for sorting on betas on our three counter-cyclical benchmark factors. Overall, we observe that the high basket has a higher average IEIR than the low basket, confirming our intuition that the inferior goods' prices grow less than the prices of the normal goods on average. In particular, sorting on the unemployment beta leads to a low (high) basket IEIR of -0.77% (-0.19%) per annum, and the spread in average IEIR between the high and the low baskets is 0.57% per annum. Similarly, we find that goods with higher covariance with economic policy uncertainty have higher IEIR. On average, prices of goods with the low (high) beta on economic policy uncertainty grow 0.74% (0.20%) less than the CPI per annum. The average IEIR difference between the high and the low baskets is 0.53% per annum.

The results in Panel B of Table 6 are organized in the same manner as in Panel A. They demonstrate that our findings are robust to using a longer rolling window of $h = 120$ months in estimating the conditional betas. Even better, the high-minus-low spreads are higher in magnitude than Panel A. Moreover, they are all statistically significant, even for basket sorts on long-term inflation forecasts and financial conditions that don't appear in Panel A's results. Overall, consumer goods with a lower average IEIR generally have prices that grow less than other goods because they covary positively with pro-cyclical factors like long-term inflation expectations, wages, and consumer sentiment more than other goods. On the other hand, they may also negatively covary with counter-cyclical factors like unemployment, economic policy uncertainty, and financial conditions.

Based on the statistically significant spreads in both panels of the table, the basket sorts suggest that a consumption strategy that focuses only on the inferior goods rather than the normal goods generates a significant purchasing power gain that is overall between 0.11% and 0.69% per annum. Moreover, if basket sorts are relative to betas on a counter-cyclical factor, this gain is between 0.31% and 0.69% per annum. Otherwise, it ranges between 0.11% and 0.40% per annum.

4.2 Fama-MacBeth regressions

We now focus on the empirical evaluation of equations (3) and (4). Using the two-pass cross-sectional regression method of Fama and MacBeth (1973, henceforth FM), we estimate the sensitivities, i.e., factor lambdas, of consumer good average IEIR to factor loadings as measured by the conditional betas. To compute conditional multivariate betas, we follow Lewellen and Nagel (2006), and instead of trying to determine the appropriate set of conditioning variables, we use short-window regressions to calculate the factor loadings. Our baseline results are based on the 60-month rolling window in estimating the conditional betas in the first stage of the FM procedure. We also provide results where betas are estimated from the 120-month rolling window. We run month-by-month cross-sectional regressions of the 146 IEIR on the corresponding betas to compute the factor lambdas. We report the time-series averages of the estimated coefficients.

The top panels of Table 7 and Table 8 show estimates of factor lambdas for the listed models. The bottom panels report for every factor f the annualized spread $\hat{E}\left[(\beta_{75^{th}f,t}-\beta_{25^{th}f,t})\lambda_{f,t}\right]$ between two hypothetical goods with different betas on the factor f, everything else equal. We refer to this number as the factor's interquartile spread (IQS). The first good's beta is the 75th percentile, while the second is the 25th percentile of the cross-sectional distribution of individual good betas on factor f. The IQS thus represents how much the prices of low beta goods grow more or less than the prices of high beta goods on average. It would be complicated to create baskets of goods that differ only in one of the multivariate betas, with everything else equal. So we look at the IQS only as an indicative number to help interpret the economic magnitude of the factor lambda reported in the FM regressions. The IQS are interpretable like the high-minus-low spreads reported in Table 6 for basket sorts. However, they are based on multivariate betas rather than univariate betas.

Focusing on Table 7, columns labelled **1**, **3** and **4** correspond to single-factor model specifications with a benchmark pro-cyclical factor. Specifically, we see negative and statistically significant factor lambdas for long-term inflation expectations, wages, and consumer sentiment. This observation is consistent with the fact that consumer goods that tend to be cheaper in economic recessions when consumers are worse off (i.e., goods with greater positive beta on pro-cyclical factors) undergo, on average, lower price increases (i.e., have lower $\mathbb{E}\left[\pi^e_{i,t}\right]$) than other goods. The other columns displaying results for single-factor specifications are related to a counter-cyclical factor. These are the columns labelled **2**, **5** and **6**. We see positive and statistically significant factor lambdas, especially for the unemployment gap and economic policy uncertainty. Likewise, this observation is consistent with the fact that consumer goods that tend to be more affordable in economic expansions when consumers are better off (i.e., goods with higher positive beta on counter-cyclical factors) are, on average, subject to higher price growth (i.e., have higher $\mathbb{E}\left[\pi^e_{i,t}\right]$) than other goods. In economic terms, the IQS of the unemployment gap is 0.27%, and its value is 0.44% for the economic policy uncertainty. Also, the IQS of the long-term inflation expectations is -0.11%, and its value is -0.20% for the wages. Notice that these IQS values are sizeable relative to the average IEIR of -0.50% for the typical consumer good as reported in Table 3, or if compared to high-minus-low IEIR spreads reported in Table 6 for the corresponding factor. For single-factor specifications, in absolute value, the IQS of our benchmark counter-cyclical factors tend to be higher than the IQS for our benchmark pro-cyclical factors. These results are also consistent with the basket sorts of Table 6.

The remaining columns of Table 7, numbered in Roman numerals from **I** to **XVI**, show results for various model specifications with more than one factor, all chosen among our six benchmark factors. The long-term inflation expectations and the unemployment gap are common factors in all these multifactor models since they are the two factors of the conventional Phillips curve model which represent the standard variables used to analyze consumption price dynamics in the extant literature. In all these specifications, estimates of factor lambdas have the right sign depending on the cyclicality of the factor, and these estimates are also highly statistically significant. This observation is true for all factors, including financial conditions, for which lambda is not statistically significant in single-factor specifications.

We qualitatively obtain very similar results when considering a 120-month rolling window estimation for the first-stage betas. They are shown in Table 8 which is structured identically to Table 7. All pro-cyclical factor lambdas remain negative, and counter-cyclical factor lambdas remain positive and highly statistically significant regardless of the model specification. In terms of economic magnitude, there is a noticeable increase in the IQS for almost all the single-factor specifications ($\mathbf{1'}$ to $\mathbf{6'}$). The economic magnitudes more or less double for unemployment gap (from 0.27% to 0.57%), wages (from −0.20% to −0.37%), consumer sentiment (from −0.16% to −0.33%), and financial conditions (from 0.09% to 0.17%) in single-factor specifications.

Overall, there is also a noticeable increase in the IQS of long-term inflation expectations, unemployment gap, and financial conditions in multifactor model specifications ($\mathbf{I'}$ to $\mathbf{XVI'}$) when the longer rolling window is used for factor loadings estimation. Especially, the economic magnitudes of long-term inflation expectations range between −0.07% and −0.23% in our baseline results and between −0.10% and −0.32% with the longer rolling window. For the unemployment gap, these two ranges are between 0.17% and 0.41%, and between 0.31% and 0.58%, respectively. Likewise, for financial conditions, the economic magnitudes range between 0.18% and 0.32% for the 60-month window scenario. The figures are between 0.27% and 0.42% for the 120-month window scenario. Once again, these IQS values are sizeable if compared to the average IEIR of −0.50% for the real price of the typical consumer good, as reported in Table 3, or relative to high-minus-low IEIR spreads reported in Table 6 for the corresponding factors.

Notice that we have chosen our benchmark factors and motivated them as the main determinants of consumer goods prices. We are now interested in knowing what percentage of the IEIR time-series variation is explained by the factors overall. We, therefore, represent in Figure 4 the median of the rolling window R^2_{adj} across consumer goods, together with their 20th and 80th percentiles. The figure proceeds from the 60-month rolling window, and the pattern for the longer 120-month window is similar. From the figure, we visualize the ability of our benchmark factors as joint determinants of individual consumer goods prices over time. Their explanatory power is the highest (a median R^2_{adj} between 40% and 55% across consumer goods) during the period corresponding to the four rounds of quantitative easing (QE) launched by the Fed to fight the financial crisis. They lasted from December 2008 to October 2014. This median explanatory power across consumer goods does not exceed 22% in non-QE periods. This observation is striking as the QE policy directly impacts financial conditions such as interest rates, inflation, unemployment, and wages, reinforcing their effects with substantial implications for the consumer sector.

To conclude this subsection, we used FM regressions to estimate the relationship between average IEIR and the IEIR betas on factors capturing common sources of variation in consumer goods prices. Our results show that, in the cross-section of consumer goods, average IEIR negatively correlates with loadings on pro-cyclical factors, i.e., with consumer goods affordability in bad times. At the same time, it is positively related to loadings on counter-cyclical factor, i.e., with consumer goods affordability in good times. The associated factor lambdas are statistically and economically significant, and their signs are stable and consistent with the theoretical predictions. Up to 26% of the heterogeneity in average IEIR among consumer goods is explained by IEIR betas on long-term inflation expectations and the unemployment gap, i.e., the two factors of the conventional Phillips curve model. Expanding this standard set of factors to wages, consumer sentiment, economic policy uncertainty, and financial conditions increases the explanatory power up to 41%. In the following subsection, we further assess the robustness of these results.

4.3 Further robustness checks

This section provides further robustness checks by considering data on fourteen additional economic indicators that we believe, similar to our six benchmark economic variables, can potentially affect consumer goods prices in the economy. These additional data descriptions are summarized in Table 2. Similar to our six benchmark factors, we build the new factors as ARMA(1,1) innovations in the original series. Likewise, we use actual factor correlations with the real GDP growth rate to classify the factors by their cyclicality. We end up with eight procyclical factors and six countercyclical factors. Notice that, given the relatively large number of the additional factors, we restrict our analysis to single-factor model specifications involving them.

We report two sets of results for each factor, one based on the 60-month rolling window estimation of the conditional betas and the other corresponding to the 120-month rolling window analysis. Three among the six additional counter-cyclical factors are different measures of the financial conditions. We use them in replacement of the NFCI into the multifactor model specifications **V** (Table 7) and **V′** (Table 8), in order to verify the robustness of our full specification results to different measures of financial conditions. This latter analysis is important, especially because a robust cross-sectional relationship between consumer goods prices and financial conditions would confirm the strong links between the macroeconomy and financial markets that are highlighted elsewhere in the macro-finance literature (e.g., Cochrane; 2005b).

The factor lambda estimation for the eight pro-cyclical factors are reported in Table 9. The left panel (Panel A) is based on the 60-month rolling window estimation of the conditional betas, and the right panel (Panel B) corresponds to the 120-month rolling window analysis. The first column lists the factor names, and the second column shows their correlations with the real GDP growth rate, from which we can see that the eight pro-cyclical factors indeed display positive correlations with the real GDP growth rate.

The first two factors in Table 9 (columns **7** and **8**, then columns **7′** and **8′**) capture variations in relative prices: the relative import price factor, $\pi_t^{(\mathrm{I})} - \pi_{0,t}$, and the relative oil price factor, $\pi_t^{(\mathrm{O})} - \pi_{0,t}$, as in Blanchard et al. (2015). These two factors embody how variations in foreign and global markets affect the domestic market for consumer goods. Their correlations with the GDP are 0.14 and 0.18, respectively. The relative oil price factor captures the pass-through of nominal exchange rates and oil prices into core inflation measures. It is perceived as a key driver of the run-up of inflation in the late seventies and the eighties. The estimated lambdas for the two relative price factors are negative in both the 60-month and 120-month scenarios. However, these lambdas are not statistically significant for the relative import price factor. At the same time, they are statistically significant at conventional levels for the relative oil price factor in both table panels.

The following three factors (columns **9**, **10** and **11**, then columns **9′**, **10′** and **11′**) are all related to industrial production: the industrial production's total index, ind_t, the industrial production's consumer goods, ipc_t, and the industrial production's durable consumer goods, ipd_t. Their correlations are 0.27, 0.23, 0.23 with the real GDP growth rate, respectively, and the associated factor lambdas are all negative and strongly statistically significant for both rolling window scenarios.

Next, we consider the growth rates in the real per capita personal income, inc_t (column **12**, then column **12′**), and in the real personal consumption expenditures, cg_t (column **13**, then column **13′**). These two factors embody how domestic consumer income and expenditure changes affect the domestic market for consumer goods. Their respective correlations with the GDP growth are 0.10 and 0.25. Both factor lambdas are estimated to have negative values and are statistically significant in the two scenarios of Table 9, except for the factor inc_t with the 60-month scenario.

The last factor in Table 9 (column **14**, then column **14′**) is the Brave-Butters-Kelley coincident index[10], bbk_t. The correlation between the factor bbk_t and the real GDP growth rate is 0.21. The associated factor lambda is negative and statistically significant at the 99% confidence level in both table panels. At this stage, the negative lambdas of the pro-cyclical factors strongly support our idea. Consumer goods with the lowest average IEIR are so because they have a higher positive beta on the pro-cyclical factors. A negative factor lambda on a more positive consumer good beta decreases the average IEIR in the cross-section.

Table 10 documents the estimation of factor lambdas for the six additional counter-cyclical factors. The table is structured identically to Table 9. The six factors belong to two main groups. The first three factors are related to different measures of economic policy uncertainty.[11] One measure is based on the overall index, cat_t (results are displayed in columns **15** and **15′**), the

[10]The Brave-Butters-Kelley Indexes (BBKI) are a research project of the Federal Reserve Bank of Chicago. The BBK coincident and leading Indexes are constructed from a collapsed dynamic factor analysis of a panel of 500 monthly measures of U.S. real economic activity and quarterly real GDP growth. The BBK coincident index is the sum of the leading and lagging subcomponents of the cycle measured in standard deviation units from trend real GDP growth. More details about this index can be found in Brave, Butters and Kelley (2019) and Brave, Cole and Kelley (2019).

[11]Available from https://www.policyuncertainty.com/. See Baker et al. (2016) for methodological details.

next measure, $eput_t$, is related to taxes (results are displayed in columns **16** and **16′**), and the last measure , $epum_t$, is related to monetary policy (results are displayed in columns **17** and **17′**). These factors correlations with the GDP growth rate are -0.17, -0.14, and -0.08. Regardless of which of these three factors is considered, the factor lambda is positive and strongly statistically significant in both scenarios of the table, consistent (with the same order of magnitude) with similar findings reported in Table 7 and Table 8 for our benchmark economic policy uncertainty factor.

The last three factors of Table 10 are related to different measures of the financial conditions. These are, the corporate bond spread, cbs_t (results displayed in columns **18** and **18′**), which is the difference between the yield on BBB-rated corporate bonds and the yield on 10-year Treasury securities, the credit spread, cs_t (column **19**, then column **19′**), and the excess bond premium, ebp_t (results displayed in columns **20** and **20′**), as constructed by Gilchrist and Zakrajšek (2012). Correlations of these factors with the GDP growth rate are -0.26, -0.20 and -0.19, respectively. To the contrary of the three economic policy uncertainty factors, the three financial conditions factor lambdas are either positive and significant only at the 90% confidence level, or negative but insignificant. However, when each of these factors is considered in replacement of the NFCI into the multifactor model specifications **V** (Table 7) and **V′** (Table 8), their factor lambdas become positive and significant overall as displayed in Table 11. This latter result is consistent with similar findings reported in Table 7 and Table 8 for our benchmark financial conditions factor, i.e, the NFCI. Our results, i.e., the positive lambdas of the counter-cyclical factors, strongly corroborate our intuition. Consumer goods with the highest average IEIR are so because they have a higher positive beta on the counter-cyclical factors. A positive factor lambda on a more positive consumer good beta increases the average IEIR in the cross-section.

4.4 The informational content of the cross-section of IEIR betas

This section connects our cross-sectional analysis with the time-series variation of the inflation risk and risk premium. The inflation risk premium is the compensation investors demand to protect themselves against inflation risk. There have been debates in academia and policy circles on the concept and measurement of the inflation risk and the inflation risk premium. It is tempting to conclude that the inflation risk premium relates to the uncertainty or volatility of inflation (see, e.g., Wright; 2011). Still, its economic determinants are more subtle in most modern pricing models. For example, in principle inflation risk premium should be positive if inflation is high in bad times. On the other hand, if inflation invariably occurs when agents are exceedingly happy, they would not need an inflation risk premium.

Our cross-sectional study gives us a natural way of measuring inflation risk throughout the IEIR betas. For example, the IEIR betas on counter-cyclical factors measure how affordable consumer goods are in good times. Hence, we expect positive variation in those betas to impact the inflation risk premium negatively. Similarly, the IEIR betas on pro-cyclical factors measure good affordability in bad times, and we expect positive variation in those betas to increase the inflation risk premium. Unfortunately, it is hard to test these intuitions as the inflation risk premium is not observable.

We consider two factors to proxy changes in the inflation risk and risk premium. First, ΔBEIR_t, which is the change in the 10-year breakeven inflation rate (BEIR) that we download from FRED (series 10YIEM). The data are annualized monthly data, and the sample period is from January 2003 to December 2019.[12] Likewise, we also consider ΔBEIR_t, which is the change in the bond beta, which we obtain by regressing the 10-year Treasury bond log returns on the S&P 500 log returns. We download the 10-year bond index and the S&P 500 index data from CRSP. Both series are monthly, and the sample period is from January 1990 to December 2019. We estimate the bond beta series using monthly rolling regressions with a 60-month window.

In principle, a change in the BEIR sums up the changes in the objective inflation expectation and the inflation risk premium. However, since central bank credibility is strong, we implicitly assume that changes in inflation expectations are negligible as long-term inflation forecasts hoover around the target. The second proxy ΔBEIR_t, implicitly assumes that inflation is the leading risk

[12]The data of the 10-year breakeven inflation rate (T10YIEM) available on FRED starts from January 2003.

for holding bonds (see Campbell et al.; 2017). Thus, the beta of bonds on stocks is related to the inflation risk premium.

Table 12 reports the regression results of changes in our inflation risk and risk premium proxies on changes in the median beta corresponding to each economic factor. We also add the changes in the inter-quintile betas to account for the cross-sectional dispersion of the betas. From a purely statistical standpoint, the results indicate an apparent link between the betas extracted from our cross-sectional exercise and the inflation risk and risk premium. For example, about 22% of the monthly variation in the break-even inflation rate and 13% of the bond beta can be attributable to variation in our cross-sectional IEIR betas. Regarding the signs and focusing on the change in the BEIR as a proxy for the change in the inflation risk premium, we find that an increase in the beta for the three counter-cyclical factors (unemployment gap, policy uncertainty, and financial conditions) translates into a decrease in the inflation risk premium. The reverse is true when looking at the three pro-cyclical factor betas (long-term inflation expectations, wages, and consumer sentiment). Likewise, except for economic policy uncertainty, increasing cross-sectional dispersion in the betas positively impacts the inflation risk premium regardless of the cyclicality of the factor.

5 Conclusion

Consumption and investment are the two main decision-making levers of a maximizing economic agent constrained by the budget or wealth. However, the literature in financial economics has focused on investment, seeking to explain both the time-series and cross-sectional variation in the returns on investment assets. As a result, very few papers deal with consumer goods prices, particularly the potential drivers of the heterogeneity of inflation rates among individual consumer goods. It is the focus of this paper.

We define a quantity of interest for an economic agent that would summarize the consumption opportunity like the asset return, which is a complete and scale-free summary of the investment opportunity. We, therefore, introduce the individual excess inflation rate (IEIR) of a consumer good as the good's individual inflation rate (IIR) minus the general inflation rate. We document considerable heterogeneity in IEIR across goods and services, which we explain by heterogeneity in IEIR loadings on a set of economic factors capturing common sources of variation in the prices of consumer goods. These economic factors are chosen based on economic rationale and following the literature exploring the main drivers of inflation dynamics.

We build on the cross-sectional asset pricing literature regarding the methodological framework and the empirical methods. Our empirical findings are significant and very robust. The results show that the average IEIR is positively related to IEIR loadings on counter-cyclical factors such as the unemployment gap, economic policy uncertainty, and financial conditions in the cross-section of consumer goods. It is the opposite for pro-cyclical factors such as long-term inflation expectations, wages, and consumer sentiment. These novel results contrast with similar findings in cross-sectional asset pricing and highlight the divergent fundamental logics that lead to economic agents' different investment and consumption behaviors.

Additional findings highlight the explanatory power of our benchmark factors in particular episodes, such as the quantitative easing period. The changing cross-sectional distribution of IEIR betas also proves relevant in explaining time-series variations in inflation risk and risk premium. We believe these to represent exciting avenues for future research.

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Table 1: **146 Goods and Services**

This table reports on the 146 categories of goods and services included in our analysis, covering general aspects of consumers' daily lives. We assume that the goods and services on the list are purchased for consumption rather than in pursuit of returns, which include non-durables and durables, because non-durables are short-lived, consumed rapidly, and unlikely to hold long enough to be resold until prices increase; durables may last longer, but due to wear and tear, as well as possible product upgrades on the market, these durables are usually purchased with the intent to consume rather than hold and resell for profit. The 146 goods and services in this table are sorted (ranking shown in column #) by their corresponding individual excess inflation rate (IEIR) in descending order. IEIR are in percentage units. Data were downloaded from the U.S. Bureau of Labor Statistics (BLS) on 17 November 2021.

#	**Goods and Services**	**IEIR**	#	**Goods and Services**	**IEIR**
1	Hospital services	3.36	***36***	Salt and other seasonings and spices	0.67
2	Delivery services	3.20	***37***	Food at employee sites and schools	0.65
3	College tuition and fees	3.18	***38***	Rent of primary residence	0.63
4	Elementary and high school tuition and fees	3.06	***39***	Admission to movies, theaters, and concerts	0.61
5	Veterinarian services	2.36	***40***	Laundry and dry cleaning services	0.58
6	Water and sewerage maintenance	2.24	***41***	Motor vehicle repair	0.58
7	Technical and business school tuition and fees	2.04	***42***	Other lodging away from home including hotels and motels	0.57
8	Housing at school, excluding board	1.99	***43***	Fresh biscuits, rolls, muffins	0.57
9	Cigarettes	1.88	***44***	Tomatoes	0.56
10	Fuel oil and other fuels	1.70	***45***	Other fresh vegetables	0.52
11	Motor vehicle insurance	1.69	***46***	Apples	0.52
12	Nursing homes and adult day services	1.67	***47***	Full service meals and snacks	0.49
13	Day care and preschool	1.60	***48***	Owners' equivalent rent of primary residence	0.46
14	Postage	1.55	***49***	Potatoes	0.46
15	Dental services	1.49	***50***	Moving, storage, freight expense	0.38
16	Admission to sporting events	1.46	***51***	Other condiments	0.29
17	Prescription drugs	1.45	***52***	Bacon, breakfast sausage, and related products	0.28
18	Garbage and trash collection	1.36	***53***	Frankfurters	0.24
19	Legal services	1.31	***54***	Other fats and oils including peanut butter	0.22
20	Funeral expenses	1.29	***55***	Fruits and vegetables	0.18
21	Cable and satellite television service	1.28	***56***	Pet food	0.17
22	Citrus fruits	1.23	***57***	Cakes, cupcakes, and cookies	0.11
23	Butter and margarine	1.07	***58***	Canned fruits and vegetables	0.09
24	Fresh fish and seafood	1.03	***59***	Services by other medical professionals	0.05
25	Fees for lessons or instructions	1.00	***60***	Cereals and bakery products	0.04
26	Other food away from home	1.00	***61***	Sauces and gravies	0.03
27	Pet services	0.93	***62***	Meats, poultry, fish, and eggs	-0.01
28	Parking and other fees	0.92	***63***	Rice, pasta, cornmeal	-0.01
29	Food at elementary and secondary schools	0.87	***64***	Other bakery products	-0.06
30	Gasoline (all types)	0.80	***65***	Airline fares	-0.08
31	Bread	0.77	***66***	Snacks	-0.11
32	Alcoholic beverages away from home	0.75	***67***	Processed fruits and vegetables	-0.12
33	Beef and veal	0.74	***68***	Flour and prepared flour mixes	-0.17
34	Physicians' services	0.71	***69***	Cheese and related products	-0.19
35	Financial services	0.70	***70***	Coffee	-0.26

Table 1: Continued from previous page

#	Goods and Services	IEIR	#	Goods and Services	IEIR
71	Soups	-0.26	***109***	Miscellaneous household products	-1.40
72	Dairy and related products	-0.29	***110***	Tires	-1.41
73	Energy services	-0.29	***111***	Frozen and freeze dried prepared foods	-1.47
74	Poultry	-0.30	***112***	Sewing machines, fabric and supplies	-1.55
75	Intercity train fare	-0.34	***113***	Watches	-1.60
76	Processed fish and seafood	-0.35	***114***	Jewelry	-1.60
77	Lettuce	-0.36	***115***	Stationery, stationery supplies, gift wrap	-1.67
78	Other uncooked poultry including turkey	-0.37	***116***	New vehicles	-1.72
79	Sugar and sweets	-0.37	***117***	Household cleaning products	-1.75
80	Ice cream and related products	-0.39	***118***	Internet services and electronic information providers	-1.76
81	Lunchmeats	-0.46	***119***	Music instruments and accessories	-1.78
82	Other dairy and related products	-0.46	***120***	Men's footwear	-1.90
83	Other food at home	-0.50	***121***	Fresh milk other than whole	-1.91
84	Frozen fruits and vegetables	-0.53	***122***	Used cars and trucks	-1.92
85	Fresh whole milk	-0.54	***123***	Women's footwear	-1.98
86	Ham	-0.56	***124***	Women's underwear, nightwear, swimwear and accessories	-2.09
87	Club membership for shopping clubs, fraternal, or other organizations, or participant sports fees	-0.56	***125***	Infants' and toddlers' apparel	-2.41
88	Alcoholic beverages at home	-0.56	***126***	Men's pants and shorts	-2.42
89	Eggs	-0.60	***127***	Women's outerwear	-2.53
90	Whiskey at home	-0.70	***128***	Women's dresses	-2.61
91	Eyeglasses and eye care	-0.79	***129***	Outdoor equipment and supplies	-2.66
92	Other fresh fruits	-0.84	***130***	Nonelectric cookware and tableware	-2.74
93	Other pork including roasts, steaks, and ribs	-0.89	***131***	Men's suits, sport coats, and outerwear	-2.78
94	Carbonated drinks	-0.92	***132***	Leased cars and trucks	-2.83
95	Pork chops	-0.97	***133***	Major appliances	-2.85
96	Nonalcoholic beverages and beverage materials	-0.98	***134***	Ship fare	-3.20
97	Salad dressing	-0.99	***135***	Men's shirts and sweaters	-3.43
98	Bananas	-1.07	***136***	Women's suits and separates	-3.53
99	Car and truck rental	-1.08	***137***	Sports equipment	-3.70
100	Sports vehicles including bicycles	-1.16	***138***	Other furniture	-4.05
101	Distilled spirits, excluding whiskey, at home	-1.17	***139***	Other appliances	-4.12
102	Other beverage materials including tea	-1.18	***140***	Window coverings	-4.40
103	Other motor fuels	-1.23	***141***	Toys, games, hobbies and playground equipment	-6.42
104	Nonfrozen noncarbonated juices and drinks	-1.23	***142***	Audio equipment	-7.60
105	Purchase of pets, pet supplies, accessories	-1.31	***143***	Photographic equipment	-9.24
106	Breakfast cereal	-1.35	***144***	Computers, peripherals, and smart home assistants	-11.15
107	Boys' and girls' footwear	-1.39	***145***	Other video equipment	-12.93
108	Men's underwear, nightwear, swimwear and accessories	-1.40	***146***	Televisions	-18.23

Table 2: **Data Description**

This table reports the data description for 146 price indices, 20 factors (6 benchmark factors and 14 additional robustness-check factors), and real GDP per capita. The first column shows the factor number, the second column displays the acronyms, the third column demonstrates the FRED code (17 out of 20 factors are from FRED, the data sources for the last three factors (without FRED code) are noted at the bottom of the table), the fourth column presents the detailed description, and the last column illustrates the data frequency.

#	Variable	FRED code	Description	Frequency
Price Indices for 146 Goods and Services				
	$P_{i,t}, i = 1, 2, ..., 146.$		From U.S. Bureau of Labor Statistics (BLS), 146 names are reported in Table 1.	Monthly
6 Benchmark Factors and 14 Robustness-Check Factors				
1_1	$\pi_t^{(\mathrm{LTE})}$	EXPINF10YR	10-Year Expected Inflation, annual percentage rate	Monthly
1_2	$\pi_{0,t-1}^*$	CPIAUCSL	Consumer Price Index for All Urban Consumers: All Items in U.S. City Average	Monthly
2_1	u_t	UNRATE	Unemployment Rate	Monthly
2_2	u_t^*	NROU (NAIRU)	Noncyclical Rate of Unemployment (Natural Rate of Unemployment)	Quarterly
3_1	w_t	A576RC1	Compensation of Employees, Received: Wage and Salary Disbursements	Monthly
3_2	pop_t	CNP16OV	Population Level	Monthly
4	s_t	UMCSENT	University of Michigan: Consumer Sentiment	Monthly
5	pu_t	USEPUINDXM	Economic Policy Uncertainty Index for United States	Monthly
6	$nfci_t$	NFCI	Chicago Fed National Financial Conditions Index	Weekly
7	$\pi_t^{(\mathrm{I})} - \pi_{0,t}$	B021RG3Q086SBEA	Imports of Goods and Services (Chain-Type Price Index)	Quarterly
8	$\pi_t^{(\mathrm{O})} - \pi_{0,t}$	WTISPLC	Spot Crude Oil Price: West Texas Intermediate (WTI)	Monthly
9	ind_t	INDPRO	Industrial Production: Total Index	Monthly
10	ipc_t	IPCONGD	Industrial Production: Consumer Goods	Monthly
11	ipd_t	IPDCONGD	Industrial Production: Durable Consumer Goods	Monthly
12	inc_t	A229RX0	Real Disposable Personal Income: Per Capita	Monthly
13	cg_t	DPCERAM1M225NBEA	Real Personal Consumption Expenditures	Monthly
14	bbk_t	BBKMCOIX	Brave-Butters-Kelley Coincident Index	Monthly
15	cat_t	CATEPUINDXM	Economic Policy Uncertainty Index: Categorical Index: Overall	Monthly
16	$eput_t$	EPUTAXES	Economic Policy Uncertainty Index: Categorical Index: Taxes	Monthly
17	$epum_t$	EPUMONETARY	Economic Policy Uncertainty Index: Categorical Index: Monetary policy	Monthly
*18**	cbs_t		Corporate Bond Spread (RBBB-RG10)	Quarterly
*19***	cs_t		Credit Spread (gz_spread)	Monthly
*20***	ebp_t		Excess Bond Premium	Monthly
	GDP	A939RX0Q048SBEA	Real gross domestic product per capita, Chained 2012 Dollars	Quarterly

*cbs_t is RBBB (yield on BBB-rated corporate bonds) minus RG10 (yield on10-year Treasury security).
Data are from FRB/US model package, which is available at the Federal Reserve Board website.
**cs_t and ebp_t are constructed by Gilchrist and Zakrajšek (2012), data are regularly updated in FEDS Note by Gilchrist et al. (2016).

Table 3: **Descriptive Statistics of Individual Excess Inflation Rate (IEIR)**

This table presents the mean, standard deviation (Std.Dev.), skewness (Skew.), excess kurtosis (Kurt.) and the real per capita GDP growth correlations of the cross-sectional mean, standard deviation (Std.Dev.), skewness (Skew.), excess kurtosis (Kurt.), and 5%, 25%, 50%(median), 75% and 95% percentiles among the 146 individual excess inflation rate (IEIR), which is constructed as $\pi^e_{i,t} \equiv \ln\left(\frac{P_{i,t}/P_{0,t}}{P_{i,t-1}/P_{0,t-1}}\right)$ (see equation (2) for other equivalent forms). The 146 individual price indices are displayed in Table 1. The mean, standard deviation, and percentiles are in percentage units. The 146 IEIR are annualized monthly data, and the sample period is from January 1990 to December 2019.

	Mean	**Std.Dev.**	**Skew.**	**Kurt.**	**5%**	**25%**	**50%**	**75%**	**95%**
Mean	−0.50	5.31	−0.42	9.24	−7.86	−2.45	−0.24	1.69	6.28
Std.Dev.	0.88	1.60	1.84	6.89	2.02	0.90	1.00	1.05	2.70
Skew.	0.54	1.57	0.08	1.67	−1.89	0.53	1.09	1.17	1.65
Kurt.	1.85	3.43	0.50	3.14	6.16	2.73	3.77	3.65	3.32
corr(π^e, gdp)	−0.19	−0.31	0.15	−0.06	0.21	−0.13	−0.18	−0.31	−0.38

Table 4: **Descriptive Statistics and Correlations for Benchmark Original Factors**

Panel A in this table presents the time-series mean, median, minimum (Min), maximum (Max), standard deviation (Std.Dev.), skewness (Skew.), excess kurtosis (Kurt.), first-order autocorrelation coefficient (AR(1)), the correlation with log real GDP per capita growth rate and the cyclicity of the corresponding original six benchmark factors. All statistics are annualized values. The mean, median, minimum, maximum, and standard deviation are in percentage units. Panel B presents correlations between the corresponding factors. All factors are annualized monthly data, and the sample period is from January 1990 to December 2019.

Panel A: Descriptive Statistics for Original Factors

	Mean	**Median**	**Min**	**Max**	**Std.Dev.**	**Skew.**	**Kurt.**	**AR(1)**	**corr**(f, gdp)	**cyclicity**
$\pi_t^{(\mathrm{LTE})} - \pi^*_{0,t-1}$	0.04	0.08	-2.50	2.64	0.86	-0.08	0.14	0.97	0.43	pro
$u_t - u_t^*$	0.79	0.34	-1.41	5.14	1.62	1.12	0.44	1.00	-0.17	counter
w_t	3.18	3.70	-6.93	8.19	2.40	-1.54	3.52	0.94	0.34	pro
s_t	0.11	1.03	-41.37	30.64	12.12	-0.64	1.26	0.82	0.40	pro
pu_t	1.21	1.74	-73.50	91.74	28.28	0.18	-0.06	0.69	-0.35	counter
fc_t	-0.41	-0.54	-1.05	2.74	0.50	3.20	13.81	0.95	-0.60	counter

Panel B: Correlations Between Original Factors

	$u_t - u_t^*$	w_t	s_t	pu_t	fc_t
$\pi_t^{(\mathrm{LTE})} - \pi^*_{0,t-1}$	-0.04	0.09	0.44	-0.19	-0.36
$u_t - u_t^*$		-0.59	0.15	-0.06	0.22
w_t			0.14	-0.09	-0.48
s_t				-0.46	-0.48
pu_t					0.44

Table 5: **Descriptive Statistics and Correlations for Benchmark Actual Factors**

Panel A in this table presents the time-series mean, median, minimum (Min), maximum (Max), standard deviation (Std.Dev.), skewness (Skew.), excess kurtosis (Kurt.), first-order autocorrelation coefficient (AR(1)), the correlation with log real GDP per capita growth rate and the cyclicity of actual factors which are the ARMA(1,1) residuals of the corresponding original six benchmark factors. All statistics are annualized values. The mean, median, minimum, maximum, and standard deviation are in percentage units. Panel B presents correlations between the actual factors. All factors are annualized monthly data, and the sample period is from January 1990 to December 2019.

Panel A: Descriptive Statistics for Actual Factors

	Mean	**Median**	**Min**	**Max**	**Std.Dev.**	**Skew.**	**Kurt.**	**AR(1)**	**corr**(fr, gdp)	**cyclicity**
$\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	0.00	0.01	-0.44	0.51	0.15	0.16	0.39	0.14	0.09	pro
$u_t - u_t^*$	0.00	0.00	-0.51	0.49	0.15	0.25	0.86	0.02	-0.40	counter
w_t	0.00	0.02	-5.19	5.43	0.82	-0.32	15.67	0.00	0.20	pro
s_t	0.00	-0.01	-20.69	26.25	6.33	0.19	1.42	0.00	0.13	pro
pu_t	0.00	-0.23	-74.72	75.78	21.61	0.01	0.92	0.00	-0.18	counter
fc_t	0.00	-0.01	-0.42	0.73	0.08	2.53	22.01	0.09	-0.11	counter

Panel B: Correlations Between Actual Factors

	$u_t - u_t^*$	w_t	s_t	pu_t	fc_t
$\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	0.07	0.03	0.14	-0.12	-0.26
$u_t - u_t^*$		-0.12	-0.06	0.07	-0.02
w_t			0.10	-0.09	-0.03
s_t				-0.29	-0.14
pu_t					0.21

Table 6: **Univariate Beta Sorting**

This table presents the univariate beta sorting results based on the six benchmark factors, the description for which is reported in Table 2. Individual consumer goods and services are sorted into two baskets, L and H, by the corresponding medians of the six univariate beta on the individual excess inflation rate (IEIR). Panel A is based on the 60-month rolling window analysis. Panel B is based on the 120-month rolling window analysis. Actual factors are the ARMA(1,1) residuals of the corresponding original factors. Average IEIR ($\mathbb{E}(\pi^e)$) and standard errors (S.E.) are in percentage units. All factors are annualized monthly data, and the sample period is from January 1990 to December 2019.

Panel A: 60-Month Window

f1 ($\pi_t^{\mathbf{LTE}} - \pi_{0,t-1}^*$)	**L**	**H**	**H-L**
β_1	-3.84	5.02	
$\mathbb{E}(\pi^e)$	-0.48	-0.48	-0.01
S.E.	0.03	0.02	0.03

f2 ($u_t - u_t^*$)	**L**	**H**	**H-L**
β_2	-2.31	3.57	
$\mathbb{E}(\pi^e)$	-0.77	-0.19	0.57
S.E.	0.03	0.02	0.03

f3 (w_t)	**L**	**H**	**H-L**
β_3	-0.99	0.56	
$\mathbb{E}(\pi^e)$	-0.32	-0.64	-0.33
S.E.	0.02	0.02	0.03

f4 (s_t)	**L**	**H**	**H-L**
β_4	-0.06	0.07	
$\mathbb{E}(\pi^e)$	-0.42	-0.53	-0.11
S.E.	0.03	0.02	0.04

f5 (pu_t)	**L**	**H**	**H-L**
β_5	-0.02	0.02	
$\mathbb{E}(\pi^e)$	-0.74	-0.20	0.53
S.E.	0.03	0.03	0.04

f6 ($nfci_t$)	**L**	**H**	**H-L**
β_6	-5.32	6.36	
$\mathbb{E}(\pi^e)$	-0.50	-0.45	0.04
S.E.	0.03	0.03	0.05

Panel B: 120-Month Window

f1 ($\pi_t^{\mathbf{LTE}} - \pi_{0,t-1}^*$)	**L**	**H**	**H-L**
β_1	-3.64	5.14	
$\mathbb{E}(\pi^e)$	-0.35	-0.62	-0.27
S.E.	0.02	0.02	0.04

f2 ($u_t - u_t^*$)	**L**	**H**	**H-L**
β_2	-2.14	4.37	
$\mathbb{E}(\pi^e)$	-0.81	-0.18	0.63
S.E.	0.02	0.02	0.04

f3 (w_t)	**L**	**H**	**H-L**
β_3	-1.10	0.44	
$\mathbb{E}(\pi^e)$	-0.29	-0.69	-0.40
S.E.	0.02	0.02	0.03

f4 (s_t)	**L**	**H**	**H-L**
β_4	-0.05	0.06	
$\mathbb{E}(\pi^e)$	-0.32	-0.64	-0.32
S.E.	0.02	0.02	0.03

f5 (pu_t)	**L**	**H**	**H-L**
β_5	-0.01	0.02	
$\mathbb{E}(\pi^e)$	-0.82	-0.13	0.69
S.E.	0.03	0.02	0.05

f6 ($nfci_t$)	**L**	**H**	**H-L**
β_6	-4.22	4.49	
$\mathbb{E}(\pi^e)$	-0.64	-0.33	0.31
S.E.	0.03	0.03	0.05

Table 7: **Fama-MacBeth Regressions for Benchmark Factors (60-Month Rolling Window)**

This table presents the factor lambda estimates from Fama-MacBeth (1973) 2^{nd} stage cross-sectional regressions of the 6 benchmark factors (upper panel), and the annualized spread $\hat{E}\left[(\beta_{75^{th}\,f,t} - \beta_{25^{th}\,f,t})\lambda_{f,t}\right]$ between two hypothetical goods with different betas on the factor f, everything else equal (lower panel). The first portfolio's beta is the 75th percentile, while that of the second is the 25th percentile of the cross-sectional distribution of individual betas on factor f. The actual factors are the ARMA(1,1) residuals of the corresponding original factors, and the analysis is based on the 60-month rolling window. The description for the six benchmark factors is reported in Table 2. Columns **1** to **6** in this table report the univariate estimation for the corresponding factors, and columns **I** to **XVI** report the corresponding estimations for all the sixteen ($2^4 = 16$) possible multi-variate specifications while holding the two Phillips curve factors, $\pi_t^{(\text{LTE})} - \pi_{0,t-1}^*$ and $u_t - u_t^*$, fixed. Factor lambda estimations are displayed in percentage units and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

	1	**2**	**3**	**4**	**5**	**6**	**I**	**II**	**III**	**IV**	**V**
Intercept	-0.49^{***}	-0.62^{***}	-0.63^{***}	-0.55^{***}	-0.60^{***}	-0.58^{***}	-0.56^{***}	-0.58^{***}	-0.60^{***}	-0.62^{***}	-0.60^{***}
	(-12.33)	(-15.14)	(-16.47)	(-13.29)	(-13.93)	(-14.16)	(-17.75)	(-20.26)	(-22.02)	(-24.09)	(-23.15)
1. $\pi_t^{(\text{LTE})} - \pi_{0,t-1}^*$	-0.04^{***}						-0.03^{**}	-0.03^{***}	-0.04^{***}	-0.05^{***}	-0.06^{***}
	(-2.80)						(-2.34)	(-2.62)	(-2.68)	(-3.79)	(-4.57)
2. $u_t - u_t^*$		0.13^{***}					0.17^{***}	0.15^{***}	0.15^{***}	0.11^{***}	0.11^{***}
		(4.51)					(6.88)	(5.68)	(5.76)	(4.41)	(4.17)
3. w_t			-0.46^{***}					-0.73^{***}	-0.67^{***}	-0.76^{***}	-0.65^{***}
			(-4.02)					(-3.86)	(-3.77)	(-4.25)	(-3.85)
4. s_t				-1.29^{*}					-2.18^{***}	-2.88^{***}	-3.21^{***}
				(-1.35)					(-2.67)	(-3.63)	(-3.87)
5. pu_t					17.55^{***}					9.76^{***}	11.32^{***}
					(5.94)					(3.50)	(3.98)
6. $nfci_t$						0.01					0.05^{***}
						(0.59)					(4.05)
R^2_{adj}	0.18	0.15	0.13	0.15	0.13	0.13	0.26	0.30	0.34	0.38	0.41
Economic magnitudes (in %) (IEIR^{75th} − IEIR^{25th} = 2.06%)											
$\pi_t^{(\text{LTE})} - \pi_{0,t-1}^*$	-0.11						-0.10	-0.09	-0.11	-0.16	-0.21
$u_t - u_t^*$		0.27					0.41	0.31	0.31	0.26	0.19
w_t			-0.20					-0.17	-0.16	-0.18	-0.17
s_t				-0.16					-0.12	-0.19	-0.19
pu_t					0.44					0.20	0.21
$nfci_t$						0.09					0.29

Table 7: Continued from previous page

	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV	XVI
Intercept	-0.58^{***}	-0.59^{***}	-0.57^{***}	-0.61^{***}	-0.58^{***}	-0.60^{***}	-0.59^{***}	-0.58^{***}	-0.60^{***}	-0.59^{***}	-0.58^{***}
	(-19.21)	(-20.20)	(-18.34)	(-22.65)	(-20.83)	(-21.05)	(-19.88)	(-19.82)	(-22.85)	(-22.09)	(-20.51)
1. $\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	-0.03^{**}	-0.06^{***}	-0.04^{***}	-0.06^{***}	-0.05^{***}	-0.05^{***}	-0.04^{***}	-0.07^{***}	-0.05^{***}	-0.07^{***}	-0.06^{***}
	(-2.15)	(-4.18)	(-3.09)	(-4.36)	(-3.31)	(-3.79)	(-3.30)	(-4.59)	(-3.79)	(-4.82)	(-4.63)
2. $u_t - u_t^*$	0.16^{***}	0.13^{***}	0.16^{***}	0.10^{***}	0.14^{***}	0.12^{***}	0.16^{***}	0.12^{***}	0.14^{***}	0.10^{***}	0.11^{***}
	(6.62)	(5.31)	(6.46)	(4.07)	(5.50)	(5.09)	(6.25)	(4.66)	(5.50)	(3.83)	(4.47)
3. w_t				-0.73^{***}	-0.60^{***}				-0.59^{***}	-0.59^{***}	
				(-4.07)	(-3.25)				(-3.58)	(-3.40)	
4. s_t	-1.93^{**}					-2.72^{***}	-2.46^{***}		-2.32^{***}		-3.23^{***}
	(-2.37)					(-3.44)	(-2.93)		(-2.71)		(-3.94)
5. pu_t		10.24^{***}		7.73^{***}		11.76^{***}		11.88^{***}		9.45^{***}	14.05^{***}
		(3.69)		(2.78)		(4.21)		(4.01)		(3.22)	(4.83)
6. $nfci_t$			0.04^{***}		0.05^{***}		0.04^{***}	0.03^{**}	0.05^{***}	0.04^{***}	0.03^{***}
			(2.74)		(3.64)		(2.89)	(2.58)	(4.27)	(3.54)	(2.83)
R^2_{adj}	0.30	0.30	0.30	0.35	0.34	0.34	0.34	0.34	0.38	0.38	0.37
Economic magnitudes (in %) (IEIR^{75th} − IEIR^{25th} $= 2.06\%$**)**											
$\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	-0.07	-0.21	-0.13	-0.20	-0.12	-0.17	-0.13	-0.23	-0.17	-0.22	-0.21
$u_t - u_t^*$	0.38	0.32	0.37	0.23	0.27	0.31	0.32	0.26	0.26	0.17	0.22
w_t				-0.17	-0.16				-0.15	-0.17	-0.20
s_t	-0.11					-0.17	-0.15		-0.12		
pu_t		0.18		0.14		0.23		0.21		0.17	0.25
$nfci_t$			0.22		0.27		0.22	0.18	0.32	0.24	0.20

Table 8: **Fama-MacBeth Regressions for Benchmark Factors (120-Month Rolling Window)**

This table presents the factor lambda estimates from Fama-MacBeth (1973) 2^{nd} stage cross-sectional regressions of the 6 benchmark factors (upper panel), and the annualized spread $\hat{E}\left[(\beta_{75^{th}f,t} - \beta_{25^{th}f,t})\lambda_{f,t}\right]$ between two hypothetical goods with different betas on the factor f, everything else equal (lower panel). The first portfolio's beta is the 75th percentile, while that of the second is the 25th percentile of the cross-sectional distribution of individual betas on factor f. The actual factors are the ARMA(1,1) residuals of the corresponding original factors, and the analysis is based on the 120-month rolling window. The description for the six benchmark factors is reported in Table 2. Columns **1** to **6** in this table report the univariate estimation for the corresponding factors, and columns **I** to **XVI** report the corresponding estimations for all the sixteen ($2^4 = 16$) possible multi-variate specifications while holding the two Phillips curve factors, $\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$ and $u_t - u_t^*$, fixed. Factor lambda estimations are displayed in percentage units and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

	1′	**2′**	**3′**	**4′**	**5′**	**6′**	**I′**	**II′**	**III′**	**IV′**	**V′**
Intercept	-0.62^{***}	-0.76^{***}	-0.76^{***}	-0.60^{***}	-0.68^{***}	-0.72^{***}	-0.67^{***}	-0.66^{***}	-0.65^{***}	-0.68^{***}	-0.68^{***}
	(-14.45)	(-18.63)	(-18.35)	(-13.57)	(-14.98)	(-16.35)	(-20.38)	(-23.49)	(-24.17)	(-25.88)	(-26.50)
1. $\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	-0.06^{***}						-0.07^{***}	-0.08^{***}	-0.06^{***}	-0.10^{***}	-0.09^{***}
	(-4.07)						(-5.28)	(-5.33)	(-4.11)	(-5.81)	(-5.59)
2. $u_t - u_t^*$		0.19^{***}					0.19^{***}	0.17^{***}	0.17^{***}	0.16^{***}	0.13^{***}
		(9.92)					(11.67)	(9.33)	(8.85)	(8.36)	(6.70)
3. w_t			-0.53^{***}					-0.30^{***}	-0.34^{***}	-0.27^{***}	-0.26^{***}
			(-7.24)					(-3.97)	(-4.45)	(-3.69)	(-3.55)
4. s_t				-5.15^{***}					-3.84^{***}	-3.05^{***}	-2.68^{***}
				(-4.83)					(-4.13)	(-3.50)	(-3.10)
5. pu_t					13.51^{***}					15.58^{***}	13.48^{***}
					(4.12)					(4.85)	(4.32)
6. $nfci_t$						0.03^{*}					0.10^{***}
						(1.55)					(6.68)
R^2_{adj}	0.19	0.12	0.13	0.16	0.09	0.14	0.23	0.27	0.29	0.32	0.35
Economic magnitudes (in %) (IEIR^{75th} − IEIR^{25th} = 2.06%)											
$\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	-0.14						-0.22	-0.21	-0.16	-0.30	-0.25
$u_t - u_t^*$		0.57					0.58	0.52	0.49	0.44	0.34
w_t			-0.37					-0.16	-0.16	-0.11	-0.09
s_t				-0.33					-0.18	-0.15	-0.13
pu_t					0.20					0.23	0.17
$nfci_t$						0.17					0.39

Table 8: Continued from previous page

	VI′	**VII′**	**VIII′**	**IX′**	**X′**	**XI′**	**XII′**	**XIII′**	**XIV′**	**XV′**	**XVI′**
Intercept	-0.65^{***}	-0.69^{***}	-0.67^{***}	-0.68^{***}	-0.66^{***}	-0.67^{***}	-0.65^{***}	-0.70^{***}	-0.66^{***}	-0.69^{***}	-0.66^{***}
	(-20.53)	(-21.73)	(-19.92)	(-25.21)	(-23.73)	(-21.64)	(-20.33)	(-22.23)	(-25.05)	(-26.11)	(-21.61)
1. $\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	-0.06^{***}	-0.10^{***}	-0.06^{***}	-0.10^{***}	-0.06^{***}	-0.10^{***}	-0.05^{***}	-0.10^{***}	-0.05^{***}	-0.10^{***}	-0.10^{***}
	(-3.96)	(-5.95)	(-4.21)	(-5.93)	(-3.90)	(-6.12)	(-3.54)	(-5.94)	(-3.56)	(-5.69)	(-6.14)
2. $u_t - u_t^*$	0.17^{***}	0.19^{***}	0.15^{***}	0.16^{***}	0.12^{***}	0.16^{***}	0.13^{***}	0.16^{***}	0.11^{***}	0.13^{***}	0.13^{***}
	(10.59)	(11.27)	(9.18)	(8.91)	(6.40)	(9.72)	(8.07)	(9.61)	(6.00)	(7.06)	(8.08)
3. w_t				-0.27^{***}	-0.32^{***}				-0.38^{***}	-0.29^{***}	
				(-3.62)	(-4.32)				(-5.14)	(-3.86)	
4. s_t	-3.11^{***}					-2.44^{***}	-2.26^{***}		-2.46^{***}		-2.38^{***}
	(-3.23)					(-2.70)	(-2.45)		(-2.75)		(-2.66)
5. pu_t		7.57^{**}		11.59^{***}		13.48^{***}		6.80^{**}		10.31^{***}	11.10^{***}
		(2.22)		(3.47)		(4.09)		(2.10)		(3.28)	(3.47)
6. $nfci_t$			0.08^{***}		0.09^{***}		0.10^{***}	0.07^{***}	0.11^{***}	0.08^{***}	0.09^{***}
			(5.18)		(6.09)		(6.46)	(4.34)	(7.20)	(5.55)	(6.08)
R^2_{adj}	0.26	0.27	0.26	0.30	0.30	0.29	0.29	0.29	0.32	0.33	0.32
Economic magnitudes (in %) (IEIR^{75th} − IEIR^{25th} = 2.06%)											
$\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	-0.16	-0.26	-0.12	-0.26	-0.10	-0.32	-0.11	-0.24	-0.11	-0.22	-0.28
$u_t - u_t^*$	0.53	0.53	0.44	0.46	0.36	0.47	0.38	0.44	0.31	0.37	0.37
w_t				-0.14	-0.16				-0.17	-0.14	-0.12
s_t	-0.16					-0.13	-0.13		-0.12		
pu_t		0.11		0.17		0.19		0.07		0.13	0.13
$nfci_t$			0.35		0.38		0.40	0.27	0.42	0.32	0.37

Table 9: **Robustness Checks: Eight Pro-Cyclical Univariate Factors**

This table presents the factor lambda estimates from Fama-MacBeth (1973) 2^{nd} stage cross-sectional regressions of the eight pro-cyclical factors for additional robustness checks, the description of which is reported in Table 2. The actual factors are the ARMA(1,1) residuals of the corresponding original factors. Panel A is based on the 60-month rolling window analysis. Panel B is based on the 120-month rolling window analysis. Factor lambda estimations are displayed in percentage units and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

		Panel A: 60-month window								**Panel B: 120-month window**							
8 factors	**corr(fr,gdp)**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**7′**	**8′**	**9′**	**10′**	**11′**	**12′**	**13′**	**14′**
Intercept		-0.60^{***}	-0.60^{***}	-0.61^{***}	-0.57^{***}	-0.65^{***}	-0.60^{***}	-0.55^{***}	-0.61^{***}	-0.76^{***}	-0.77^{***}	-0.64^{***}	-0.61^{***}	-0.66^{***}	-0.70^{***}	-0.37^{***}	-0.69^{***}
		(-16.56)	(-18.61)	(-19.22)	(-16.23)	(-19.15)	(-14.48)	(-13.43)	(-16.17)	(-18.42)	(-22.39)	(-19.64)	(-16.05)	(-20.00)	(-16.48)	(-8.65)	(-15.41)
7. $\pi_t^{(I)} - \pi_{0,t}$	0.14	-0.24								-0.12							
		(-1.05)								(-0.40)							
8. $\pi_t^{(O)} - \pi_{0,t}$	0.18		-5.98^{***}								-3.13^{**}						
			(-4.19)								(-2.01)						
9. ind_t	0.27			-0.65^{***}								-0.67^{***}					
				(-5.54)								(-6.63)					
10. ipc_t	0.23				-0.76^{***}								-0.78^{***}				
					(-5.87)								(-7.05)				
11. ipd_t	0.23					-1.04^{***}								-1.77^{***}			
						(-2.94)								(-6.36)			
12. inc_t	0.10						0.09								-0.74^{***}		
							(0.59)								(-3.90)		
13. cg_t	0.25							-0.16^{**}								-0.12^{***}	
								(-2.28)								(-4.84)	
14. bbk_t	0.21								-19.58^{***}								-20.43^{***}
									(-5.01)								(-6.00)
R^2_{adj}		0.14	0.14	0.16	0.12	0.12	0.09	0.10	0.16	0.12	0.07	0.08	0.07	0.08	0.08	0.18	0.11

Table 10: **Robustness Checks: Six Counter-Cyclical Univariate Factors**

This table presents the factor lambda estimates from Fama-MacBeth (1973) 2^{nd} stage cross-sectional regressions of the six counter-cyclical factors for additional robustness checks, the description of which is reported in Table 2. The actual factors are the ARMA(1,1) residuals of the corresponding original factors. Panel A is based on the 60-month rolling window analysis. Panel B is based on the 120-month rolling window analysis. Factor lambda estimations are displayed in percentage units and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

		Panel A: 60-month window						**Panel B: 120-month window**					
6 factors	**corr(fr,gdp)**	**15**	**16**	**17**	**18**	**19**	**20**	**15′**	**16′**	**17′**	**18′**	**19′**	**20′**
Intercept		-0.54^{***}	-0.53^{***}	-0.55^{***}	-0.59^{***}	-0.54^{***}	-0.57^{***}	-0.66^{***}	-0.65^{***}	-0.70^{***}	-0.70^{***}	-0.68^{***}	-0.70^{***}
		(-13.11)	(-13.23)	(-13.66)	(-14.90)	(-13.04)	(-13.78)	(-14.30)	(-14.32)	(-16.83)	(-16.25)	(-15.46)	(-15.97)
15. cat_t	-0.17	26.01^{***}						14.23^{***}					
		(5.07)						(2.56)					
16. $eput_t$	-0.14		31.13^{***}						27.96^{***}				
			(4.69)						(3.83)				
17. $epum_t$	-0.08			42.50^{***}						19.95^{*}			
				(3.81)						(1.58)			
18. cbs_t	-0.26				0.04^{*}						0.04^{*}		
					(1.51)						(1.46)		
19. cs_t	-0.20					-0.02						0.06^{*}	
						(-0.61)						(1.43)	
20. ebp_t	-0.19						0.03						0.06^{*}
							(0.63)						(1.52)
R^2_{adj}		0.13	0.13	0.16	0.15	0.16	0.16	0.10	0.11	0.12	0.11	0.14	0.13

Table 11: **Robustness Checks: Three Alternatives to Financial Condition Factor,** $nfci$

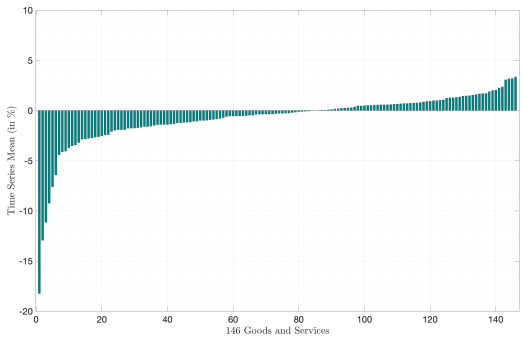
This table presents the factor lambda estimates from Fama-MacBeth (1973) 2^{nd} stage cross-sectional regressions of the 3 alternatives, *cbs*, *cs* and *ebp*, to the financial condition factor $nfci_t$ in the benchmark model, for additional robustness checks, the description of which is reported in Table 2. The actual factors are the ARMA(1,1) residuals of the corresponding original factors. Panel A is based on 60-month rolling window analysis. Panel B is based on 120-month rolling window analysis. Factor lambda estimations are displayed in percentage units and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

	Panel A: 60-month window			**Panel B: 120-month window**		
	cbs	**cs**	**ebp**	**cbs**	**cs**	**ebp**
$Intercept$	-0.60^{***}	-0.56^{***}	-0.59^{***}	-0.65^{***}	-0.64^{***}	-0.64^{***}
	(-25.83)	(-20.90)	(-23.18)	(-25.15)	(-23.75)	(-23.55)
$\pi_t^{(\text{LTE})} - \pi_{0,t-1}^{*}$	-0.03^{**}	-0.03^{**}	-0.03^{*}	-0.09^{***}	-0.07^{***}	-0.05^{***}
	(-2.14)	(-2.03)	(-1.76)	(-5.86)	(-4.11)	(-3.45)
$u_t - u_t^{*}$	0.11^{***}	0.13^{***}	0.11^{***}	0.14^{***}	0.16^{***}	0.15^{***}
	(4.49)	(5.14)	(4.42)	(7.56)	(8.23)	(7.72)
w_t	-0.76^{***}	-0.66^{***}	-0.79^{***}	-0.27^{***}	-0.27^{***}	-0.21^{***}
	(-4.68)	(-3.83)	(-4.49)	(-4.03)	(-3.76)	(-3.09)
s_t	-2.40^{***}	-2.29^{***}	-2.27^{***}	-3.80^{***}	-3.23^{***}	-3.28^{***}
	(-3.05)	(-2.82)	(-2.93)	(-4.52)	(-3.88)	(-4.04)
pu_t	7.84^{***}	9.02^{***}	7.05^{***}	17.39^{***}	16.01^{***}	14.96^{***}
	(2.70)	(3.38)	(2.75)	(5.43)	(5.34)	(5.22)
fc_t	0.09^{***}	0.13^{***}	0.10^{***}	0.00	0.09^{**}	0.09^{**}
	(3.32)	(4.02)	(3.11)	(0.01)	(2.38)	(2.47)
R^2_{adj}	0.42	0.42	0.42	0.35	0.35	0.35

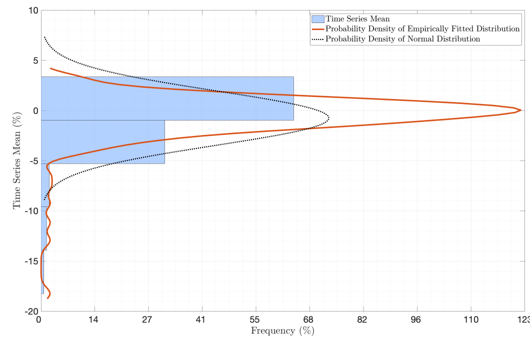
Table 12: **Link to Inflation Risk and Risk Premium (60-Month Rolling Window)**

This table presents the results of the regression of changes in the inflation risk premium proxies on the beta changes corresponding to the six benchmark factors. Dependent variables are two proxies: **BEIR**, which is the log change of 10-year breakeven inflation, and **BondMkt**, which is the change of rolling window beta from regressing the log price change of the 10-Year Treasury Bond on the log index change of S&P500. Independent variables are the changes in median $\Delta\beta_t^{50th}$ and changes in "interquartile" $\Delta(\beta_t^{80th} - \beta_t^{20th})$ of the corresponding actual factors. The analysis is based on the 60-month rolling window. Estimations are displayed in percentage units and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annualized monthly data, the sample period of **BEIR** is from January 2003 to December 2019, and the sample period of **BondMkt** is from January 1990 to December 2019.

Factor	**Regressor**	**BEIR**	**BondMkt**
	Intercept	0.00	-0.18^{***}
		(−1.07)	(−7.32)
$\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	$\Delta\beta_{\pi,t}^{50th}$	0.05^{***}	0.03
		(7.87)	(0.39)
$u_t - u_t^*$	$\Delta\beta_{u,t}^{50th}$	-0.06^{***}	−0.10
		(−5.34)	(−1.04)
w_t	$\Delta\beta_{w,t}^{50th}$	0.06	−0.13
		(1.16)	(−0.44)
s_t	$\Delta\beta_{s,t}^{50th}$	4.38^{***}	-32.12^{***}
		(5.22)	(−6.95)
pu_t	$\Delta\beta_{pu,t}^{50th}$	-8.99^{***}	88.03^{***}
		(−6.89)	(4.69)
$nfci_t$	$\Delta\beta_{fc,t}^{50th}$	-0.06^{***}	-0.10^{***}
		(−5.91)	(−2.40)
$\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	$\Delta\left(\beta_{\pi,t}^{80th} - \beta_{\pi,t}^{20th}\right)$	0.01^{**}	0.12^{***}
		(1.93)	(3.10)
$u_t - u_t^*$	$\Delta\left(\beta_{u,t}^{80th} - \beta_{u,t}^{20th}\right)$	0.01^{***}	-0.19^{***}
		(5.96)	(−3.91)
w_t	$\Delta\left(\beta_{w,t}^{80th} - \beta_{w,t}^{20th}\right)$	0.07^{***}	1.18^{***}
		(3.88)	(9.53)
s_t	$\Delta\left(\beta_{s,t}^{80th} - \beta_{s,t}^{20th}\right)$	3.93^{***}	-15.32^{***}
		(21.24)	(−8.22)
pu_t	$\Delta\left(\beta_{pu,t}^{80th} - \beta_{pu,t}^{20th}\right)$	-3.51^{***}	18.46^{***}
		(−8.15)	(2.99)
$nfci_t$	$\Delta\left(\beta_{fc,t}^{80th} - \beta_{fc,t}^{20th}\right)$	0.01^{***}	0.16^{***}
		(4.10)	(5.90)
R^2_{adj}		0.22	0.13



(a) Sorted Time Series Mean of IEIR



(b) Time Series Mean of IEIR Histogram

Figure 1: **Time Series Mean of Individual Excess Inflation Rate (IEIR)**
The 146 categories of goods and services are reported in Table 1. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

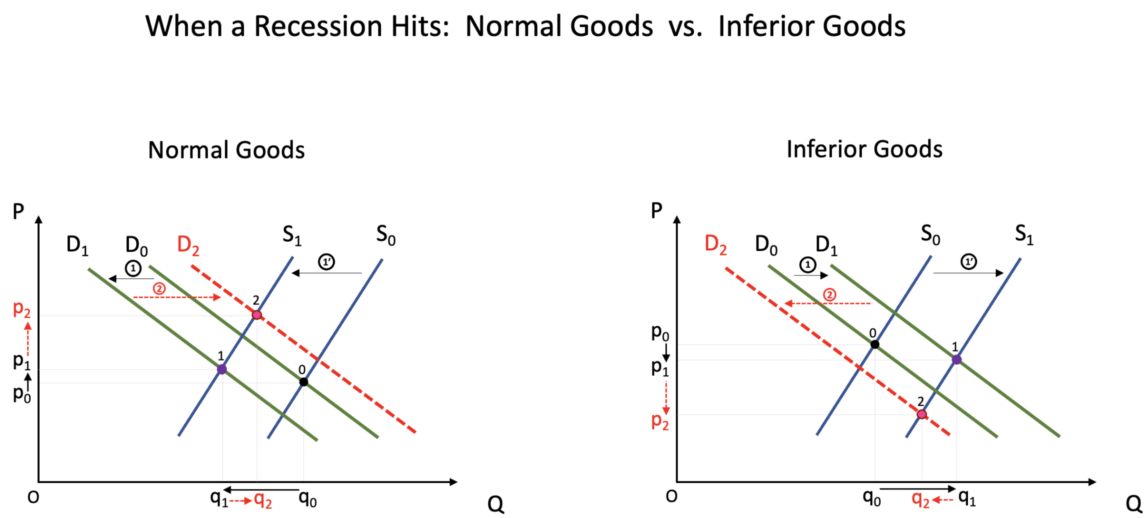
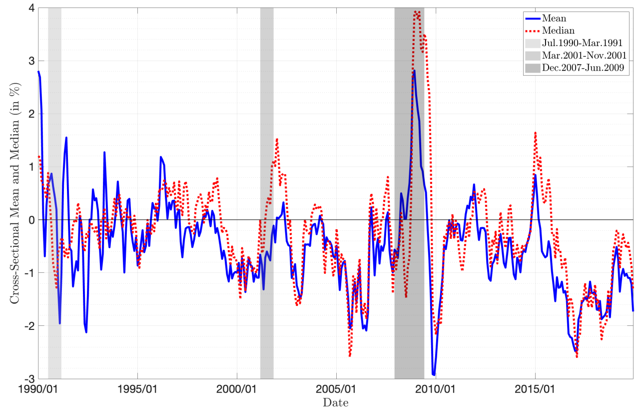
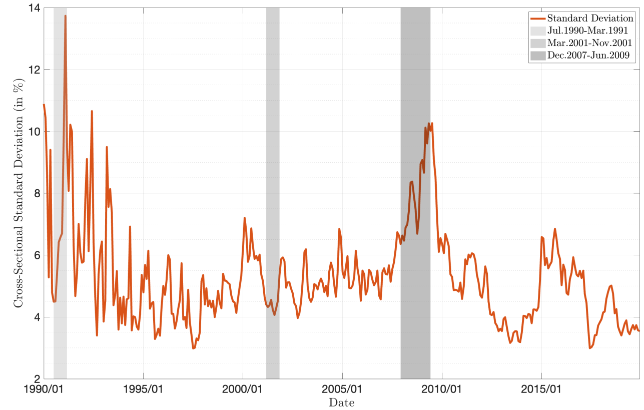


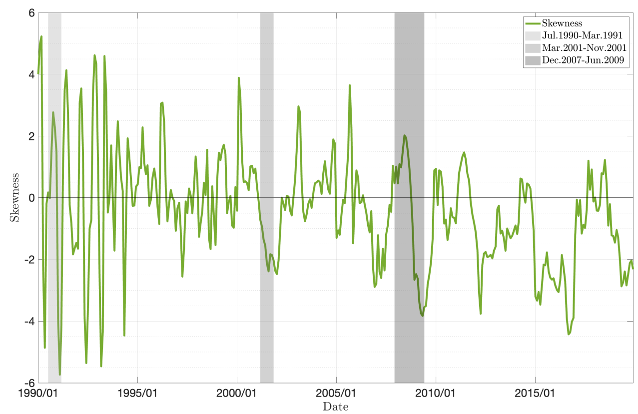
Figure 2: **The Effect of an Recession on inferior goods and normal goods**
This figure illustrates the impact of a recession on normal goods (left panel) and inferior goods (right panel), with price marked on the vertical axis and quantity of consumption marked on the horizontal axis. When a recession hits, consumers' revenue is reduced in general, subject to falling budget constraints, consumers have to reduce their consumption of expensive goods (normal goods), replace them with cheap goods (inferior goods), which shift the demand curve of normal goods to the left and inferior goods to the right (①), from D_0 to D_1. The shift ① then prompts producers to supply less expensive goods (normal goods) and more cheap goods (inferior goods), which means that the supply curve of normal goods shifts to the left and inferior goods shifts to the right (①′), from S_0 to S_1. These two shifts (① and ①′) lead to a lower equalibrium consumption for normal goods and a higher equalibrium consumption for inferior goods in recession; the equilibrium price p_1 in recession, for normal goods, it could be higher, and for inferior goods, it could be lower than p_0. When recession ends, consumers expect higher revenues than that in recessions, consumers are better off to afford goods they prefer in general (normal goods), the higher (lower) consumption willingness on normal (inferior) goods will shift the demand curve for normal (inferior) goods to the right (left), from D_1 to D_2, as shown by the dash line shift ②, before the supply curve S_1 moves, it will drive the expected equilibrium price up (down) from p_1 to p_2. The expected equilibrium consumption will increase (decrease) from q_1 to q_2, which implies a higher (lower) IEIR.



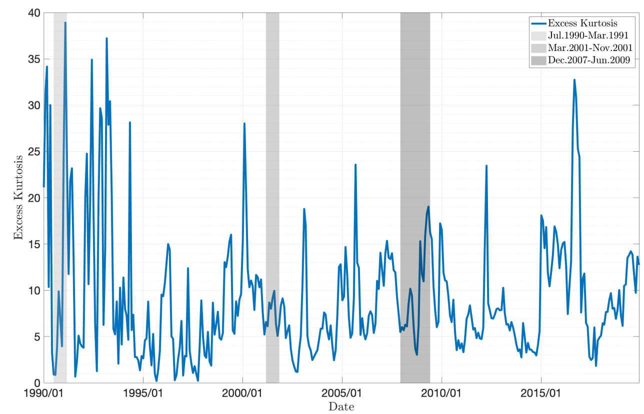
(a) Cross-Sectional Mean and Median of IEIR



(b) Cross-Sectional Standard Deviation of IEIR



(c) Cross-Sectional Skewness of IEIR



(d) Cross-Sectional Excess Kurtosis of IEIR

Figure 3: **Time Series Plots of Cross-Sectional Moments of Individual Excess Inflation Rate (IEIR)** The 146 categories of goods and services are reported in Table 1. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

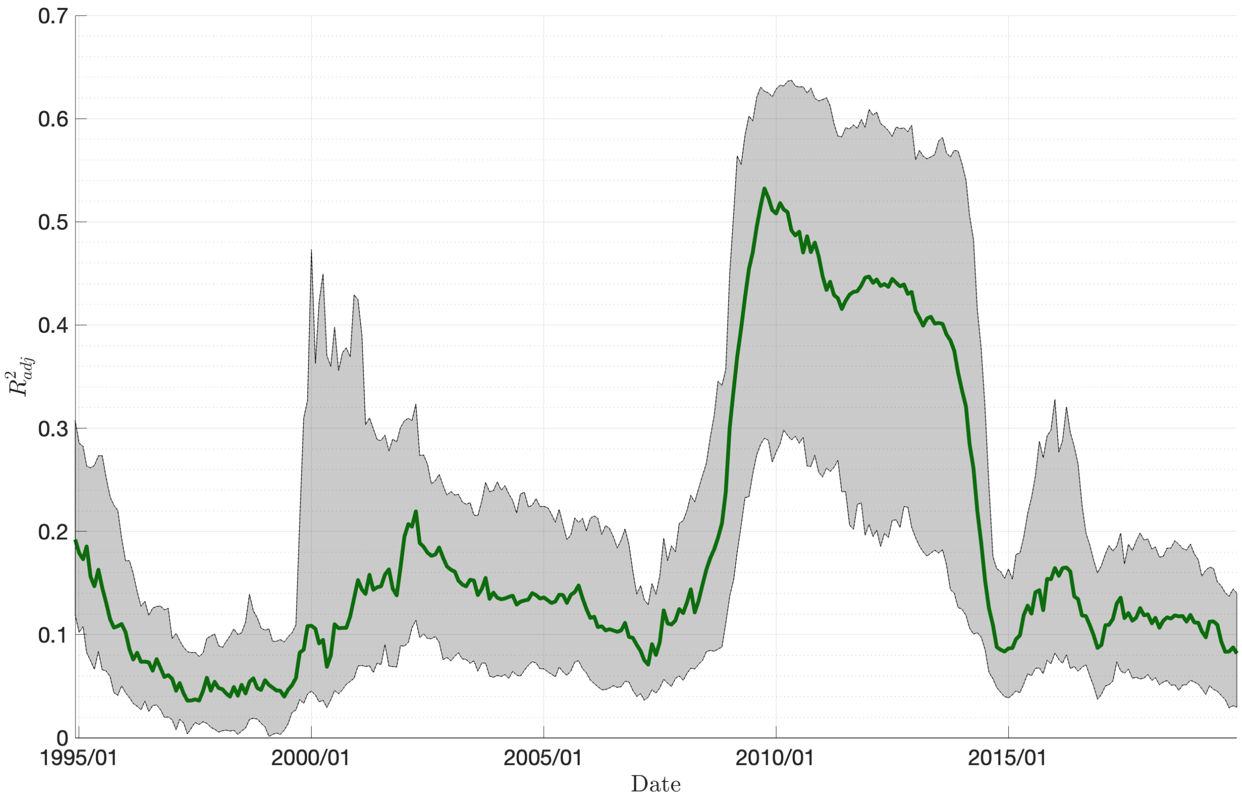


Figure 4: **Time Series Plot of Goodness of Fit (R^2_{adj}) from Time Series Regressions**
The plot of R^2_{adj} (across 146 goods and services) is the median of the adjusted goodness of fit from Fama-MacBeth (1973) 1^{st} stage time-series regressions of model **V** (based on the 60-month rolling window), with shaded 1st and 5th quintile confidence bound.

Internet Appendices for

"A cross-sectional analysis of individual goods inflation rates"

Bingxin Xing* — *ESSEC Business School*

Bruno Feunou† — *Bank of Canada*

Roméo Tédongap‡ — *ESSEC Business School*

May 13, 2022

Abstract

This document contains supplementary material, additional studies, and robustness checks that are relevant or briefly discussed in the main paper. Precisely, it consists of four sets of further analyses: Appendix A reports supplementary material and more details to the article; Appendix B provides the results based on individual inflation rates (IIR), in contrast with those of the individual excess inflation rates (IEIR); Appendix C presents the IEIR analysis of 142 goods and services (142 out of the 146 categories in the paper); finally, Appendix D shows the study of investment assets (based on the six benchmark factors) and compares them to those of consumer goods.

*Department of Finance, ESSEC Business School, 3 Avenue Bernard Hirsch, CS 50105 CERGY, 95021 Cergy-Pontoise Cedex, France. Email: bingxin.xing@essec.edu.

†Bank of Canada, Financial Markets Department, 234 Wellington Street, Ottawa ON K1A 0G9, Canada. Email: BFeunou@bank-banque-canada.ca.

‡Corresponding author: Department of Finance, ESSEC Business School, 3 Avenue Bernard Hirsch, CS 50105 CERGY, 95021 Cergy-Pontoise Cedex, France. Email: tedongap@essec.edu.

Appendix A Supplemental details

A.1 Real GDP per capita growth

To measure the cyclicity of our selected factors, we use the correlations between the actual factors[1] and the real GDP per capita growth rate. Figure A1 shows that the real GDP per capita growth rate captures the business cycles when a recession hits (marked by shaded NBER recessions)[2], the real GDP growth rate falls, followed by the recovery, corresponding to the GDP increasing after a contraction and a trough in the business cycle.

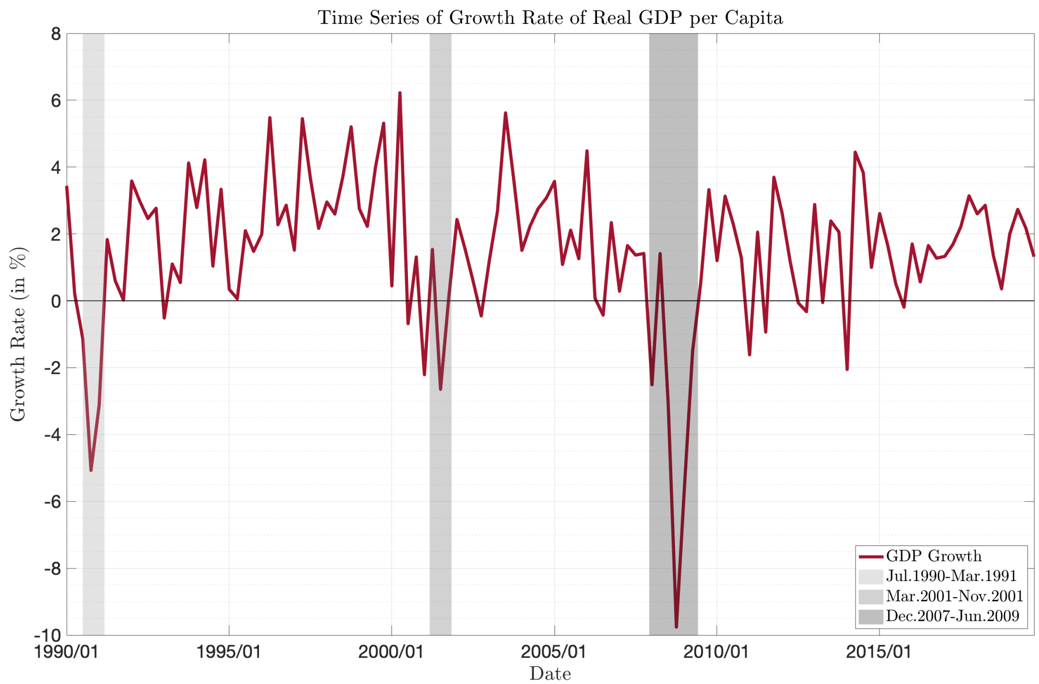


Figure A1: **Growth Rate of real GDP per Capita**

[1] Actual factors should be considered innovations in the original variables since economic agents are primarily concerned with deviations from their predictions about economic variables. We measure factor innovations by the residuals from univariate ARMA(1,1) models estimated on the original factors, so actual factors are ARMA(1,1) residuals of original factors.

[2] In the United States, it is generally accepted that the National Bureau of Economic Research (NBER) is the final arbiter of the dates of the peaks and troughs of the business cycle. The NBER identifies a recession as “a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production.”

A.2 Betas

The paper defines the consumer good's individual excess inflation rate (IEIR) as the individual good inflation rate (IIR) minus the general inflation rate. We document considerable heterogeneity in IEIR across goods and services, which we explain by the heterogeneity in IEIR loadings on a set of economic factors capturing common sources of variation in the prices of consumer goods. In this section, we analyze the time-varying estimates of factor loadings based on the univariate model and the six-factor model defined by equation (6) through Fama and MacBeth (1973, henceforth FM) 1st stage time-series regressions. We adopted two types of rolling windows: the 60-month and the 120-month window, respectively. The factor loadings depend on consumer good i, on factor k, but also on time t.

Table A2 shows that the average cross-sectional correlations between the betas of the six-factor model over the sample period are, in general, lower than those between the univariate betas. It implies that when other factors are controlled, the magnitudes of correlations (absolute values of the correlations) are reduced. Hence, using these multivariate betas in the cross-sectional regressions in the 2nd stage FM procedure reduces the problem of multicollinearity. Figure A2-1 plots the 146 sorted time-series averages of factor loadings from the six-factor model, derived from the FM through 60-window (top panel) and 120-window (bottom panel). The figure illustrates well the considerable variation of these factor loadings in the cross-section explained in the paper, regardless of the chosen estimation window. Figure A2-2 plots the time series of betas based on the 60-month window (top panel) and 120-month window (bottom panel). Each of the six plots represents goods' exposures to the corresponding benchmark economic factors. It shows significant time-series and cross-sectional variations in those betas, especially the substantial changes around the 2008 financial crisis. Specifically, the factor loadings on long-term inflation expectations, unemployment gap, consumer sentiment, and economic uncertainty jumped around 2008; on the contrary, the factor loading on wage and salary disbursements had a sudden drop around the financial crisis, while the decrease was relatively mild for the factor loading on the National Financial Conditions Index.

Table A2: **Correlation of Factor Loadings**

This table presents the average cross-sectional correlations between univariate beta (left sub-tables) and six-factor-model β defined by equation (5) (right sub-tables), the description of the factors is reported in Table 2. At every month $t \geq h$, we calculate the cross-sectional correlations between the estimated risk measures using daily data from month $t-h+1$ to t. The reported values are the time-series averages of these cross-sectional correlations over the sample. The actual factors are the ARMA(1,1) residuals of the corresponding factors. Panel A is based on $h = 60$ month rolling window analysis. Panel B is based on $h = 120$ month rolling window analysis. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

Panel A: 60-month window

univariate β

	$u_t - u_t^*$	w_t	s_t	pu_t	fc_t
$\pi^{\text{LTE}} - \pi^*_{0,t-1}$	0.22	-0.25	0.56	-0.26	-0.10
$u_t - u_t^*$		-0.56	0.03	0.07	-0.25
w_t			0.08	-0.14	0.13
s_t				-0.55	-0.26
pu_t					0.30

six-factor-model β

	$u_t - u_t^*$	w_t	s_t	pu_t	fc_t
$\pi^{\text{LTE}} - \pi^*_{0,t-1}$	0.24	-0.33	0.43	0.04	0.28
$u_t - u_t^*$		-0.43	0.15	0.18	0.01
w_t			-0.05	-0.05	0.02
s_t				0.01	0.13
pu_t					-0.04

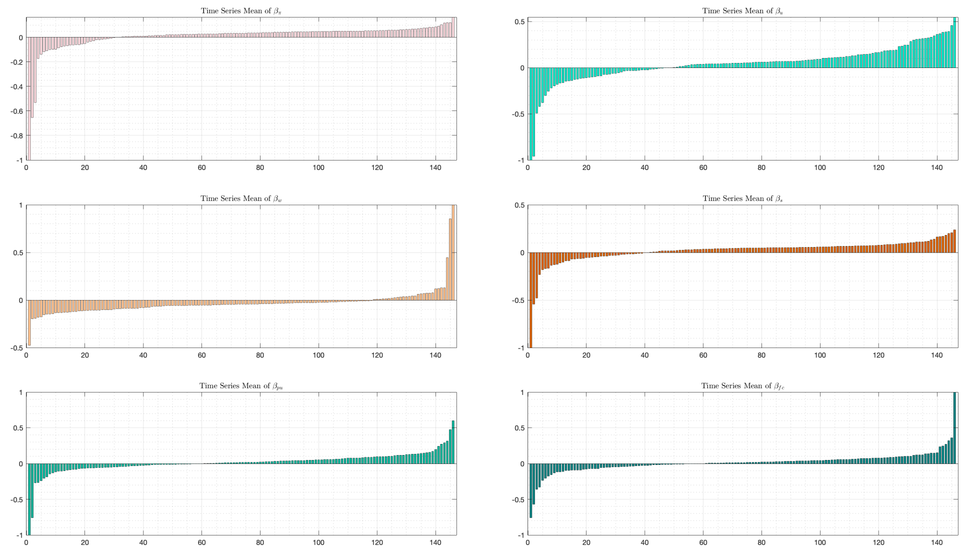
Panel B: 120-month window

univariate β

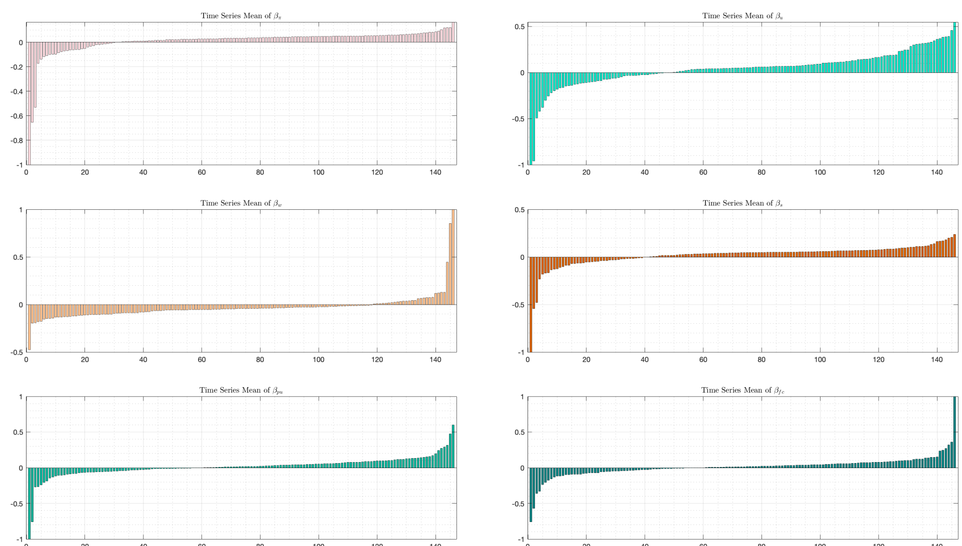
	$u_t - u_t^*$	w_t	s_t	pu_t	fc_t
$\pi^{\text{LTE}} - \pi^*_{0,t-1}$	0.39	-0.54	0.79	-0.61	-0.54
$u_t - u_t^*$		-0.71	0.20	0.12	-0.29
w_t			-0.26	0.07	0.34
s_t				-0.69	-0.55
pu_t					0.47

six-factor-model β

	$u_t - u_t^*$	w_t	s_t	pu_t	fc_t
$\pi^{\text{LTE}} - \pi^*_{0,t-1}$	0.34	-0.53	0.57	-0.13	-0.07
$u_t - u_t^*$		-0.49	0.31	0.23	0.17
w_t			-0.34	0.01	0.01
s_t				0.18	-0.03
pu_t					-0.01

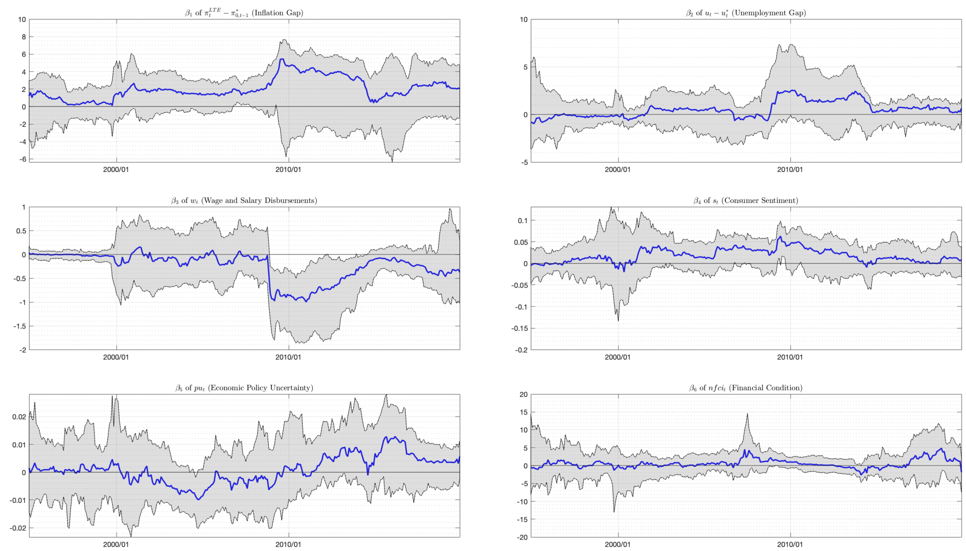


(a) Sorted Time Series Mean of the Six-factor-model β (Based on 60-month Window)

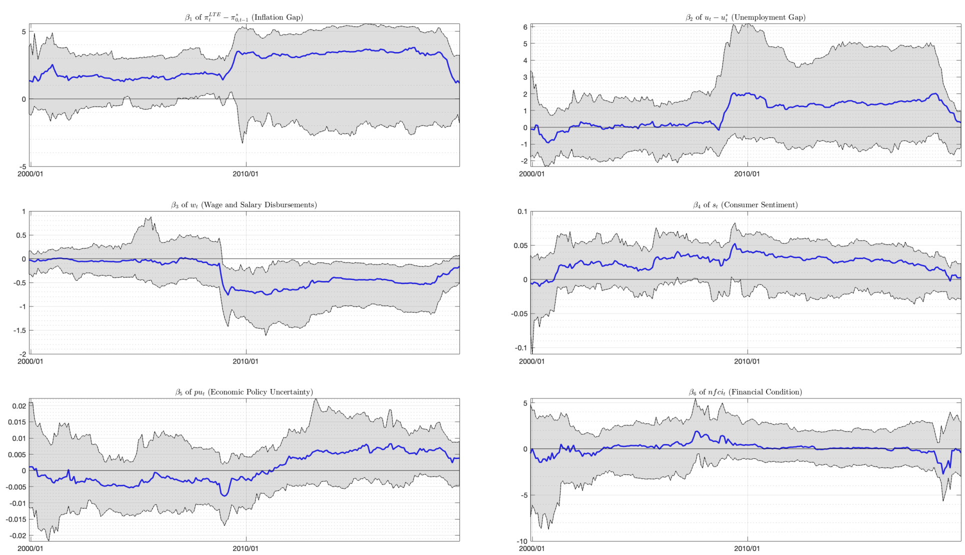


(b) Sorted Time Series Mean of the Six-factor-model β (Based on 120-month Window)

Figure A2-1: **Sorted Time Series Mean of the Six-Factor-Model Factor Loadings**
Factor loadings (βs) are scaled to 1 for easier comparison. The 146 categories of goods and services are reported in Table 1. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.



(a) Six-factor-model β (Based on 60-month Window)



(b) Six-factor-model β (Based on 120-month Window)

Figure A2-2: **Time Varying Beta**
In each plot, we draw the time series of the 20th, 50th and 80th percentile across i. The 146 categories of goods and services are reported in Table 1. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

Appendix B Analysis on 146 Individual Inflation Rates (IIR)

This section replicates the analysis based on individual inflation rates (IIR), $\pi_{i,t} \equiv \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$, which is defined by Equation (1) in the paper. The goods and services are the same as the 146 categories of goods and services in the paper, and the sample period is also the same from January 1990 to December 2019. Unsurprisingly, the IIR, like the IEIR, differs significantly in cross-section. Figure B1 plots the sample averages of the 146 IIR time series that we analyze in the paper and the IIR histogram. The minimum and maximum average IIR are -16.11% and 5.59%, respectively. The figure illustrates well the considerable variation of these values in the cross-section of IIR.

Table B1 presents the descriptive statistics of the 146 IIR series. A typical good price grows annually at 1.91%, and the 5th percentile averages −5.45% while the 95th percentile averages 8.70% through time, a difference of 14.15% (for IEIR, the difference is 14.14%), and these 5th and 95th percentiles are very large compared to the median IIR that averages to 2.18% through time, illustrating that an IIR of a consumer good is likely to be more extreme than normal, and this is again confirmed by the large IIR cross-sectional excess kurtosis that averages 9.24 through time.

In Figure B2, we plot the time series patterns of the cross-sectional moments of the IEIR and highlight the NBER recessions. These cross-sectional moments show substantial time-series variations, as confirmed by the IIR descriptive statistics in Table B1.

Based on the six benchmark factors selected in the paper, the two-group univariate beta sorting results shown in Table B2 and FM cross-section regression results through the 60-month and 120-month rolling windows shown in Table B3 and Table B4, respectively, confirmed the theory again that pro-cyclical factors: long-term inflation expectations, wages, and consumer sentiment have significant and robust negative factor lambdas, while counter-cyclical factors: unemployment, economic policy uncertainty, and financial conditions have significant and robust positive factor lambdas, regardless of the model specification. The findings are robust and stronger when using a longer rolling window of 120 months in estimating the conditional betas. Also, the economic magnitudes are considerable compared to the reference point of 1.68%.

Further robustness checks of eight pro-cyclical factors shown in Table B5 and six counter-cyclical factors shown in Table B6 reconfirm the findings based on IEIR, whether the analysis is based on the 60-month rolling window or 120-month window. However, the univariate factor lambdas for the three alternatives of financial conditions: corporate bond spread, credit spread, and excess bond premium, are not significant, but when we consider them in the six-factor model, besides *cbs* based on the 120-month rolling window analysis, the factor lambdas are all positive and significant as shown in Table B7.

Table B8 reports the regression results of changes in our inflation risk and risk premium proxies on changes in the median beta corresponding to each economic factor. In general, they are consistent with IEIR results, besides the slope of wages turned negative and significant.

Figure B3 shows a similar pattern but lower in magnitude than that in Figure 4 of the paper: the average explanatory power is the highest (a median adjusted goodness of fit, R^2_{adj}, between 24% and 33% across consumer goods) during the period corresponding to the four rounds of quantitative easing (QE) lanched by the FED to fight against the financial crisis.

In conclusion, the cross-sectional analysis based on IIR is highly consistent with that on IEIR; IIR is like the "nominal" individual inflation rate without taking the general inflation rate into consideration, and, in this sense, IEIR is analogous to the "real" individual inflation rate, furthermore, no matter in "nominal" terms or "real" terms, we document sizeable cross-sectional heterogeneity individual inflation rate among goods and services, which we explain by the heterogeneity in the exposure to a set of economic factors capturing common sources of variation in the prices of consumer goods. The empirical findings are significant and robust, confirming that goods with counter-cyclical price fluctuations have a higher inflation rate on average, and goods with pro-cyclical price fluctuations have a lower inflation rate than others. In addition, economic factors that explain this heterogeneity include pro-cyclical factors, such as long-term inflation expectations, wages, and consumer sentiment; counter-cyclical factors, such as the unemployment gap, economic policy uncertainty, and financial condition measures.

Table B1: **Descriptive Statistics of Individual Inflation Rate (IIR)**

This table presents the mean, standard deviation (Std.Dev.), skewness (Skew.), excess kurtosis (Kurt.) and the real per capita GDP growth correlations of the cross-sectional mean, standard deviation (Std.Dev.), skewness (Skew.), excess kurtosis (Kurt.), and 5%, 25%, 50%(median), 75% and 95% percentiles among the 146 individual inflation rates (IIR), which is constructed as $\pi_{i,t} \equiv \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$ (defined by Equation (1) in the paper). The 146 individual price indices included in our study are downloaded from the U.S. Bureau of Labor Statistics (BLS), and the names of which are summarized in Table 1 in the paper. The mean, standard deviation, and percentiles are in percentage units. IIR are annualized monthly data, and the sample period is from January 1990 to December 2019.

	Mean	**Std.Dev.**	**Skew.**	**Kurt.**	**5%**	**25%**	**50%**	**75%**	**95%**
Mean	1.91	5.31	−0.42	9.24	−5.45	−0.03	2.18	4.10	8.70
Std.Dev.	1.52	1.60	1.84	6.89	2.67	1.24	1.18	1.39	3.30
Skew.	0.89	1.57	0.08	1.67	−2.01	0.24	0.58	1.05	1.64
Kurt.	2.04	3.43	0.50	3.14	7.35	1.34	0.76	1.49	3.36
corr(IIR, gdp)	−0.18	−0.31	0.15	−0.06	0.12	−0.18	−0.24	−0.31	−0.35

Table B2: **Univariate Beta Sorting**

This table presents the univariate beta sorting results based on the six benchmark factors, the description for which is reported in Table 2. Individual consumer goods and services are sorted into two baskets, H and L, by the corresponding medians of the six univariate beta on the individual inflation rate (IIR). Panel A is based on the 60-month rolling window analysis. Panel B is based on the 120-month rolling window analysis. Actual factors are the ARMA(1,1) residuals of the corresponding original factors. Average IIR ($\mathbb{E}$(IIR)) and standard errors (S.E.) are in percentage units. All factors are annualized monthly data, and the sample period is from January 1990 to December 2019.

Panel A: 60-Month Window

f1 ($\pi_t^{\mathbf{LTE}} - \pi_{0,t-1}^*$)	**L**	**H**	**H-L**
β_1	-6.52	2.29	
$\mathbb{E}$(IIR)	1.82	1.81	-0.02
S.E.	0.05	0.04	0.03

f2 ($u_t - u_t^*$)	**L**	**H**	**H-L**
β_2	-2.65	3.18	
$\mathbb{E}$(IIR)	1.52	2.11	0.58
S.E.	0.05	0.04	0.03

f3 (w_t)	**L**	**H**	**H-L**
β_3	-0.83	0.71	
$\mathbb{E}$(IIR)	1.98	1.65	-0.33
S.E.	0.04	0.05	0.03

f4 (s_t)	**L**	**H**	**H-L**
β_4	-0.08	0.04	
$\mathbb{E}$(IIR)	1.87	1.76	-0.11
S.E.	0.04	0.05	0.04

f5 (pu_t)	**L**	**H**	**H-L**
β_5	-0.01	0.02	
$\mathbb{E}$(IIR)	1.55	2.10	0.55
S.E.	0.06	0.04	0.04

f6 ($nfci_t$)	**L**	**H**	**H-L**
β_6	-4.70	6.91	
$\mathbb{E}$(IIR)	1.80	1.83	0.03
S.E.	0.05	0.04	0.05

Panel B: 120-Month Window

f1 ($\pi_t^{\mathbf{LTE}} - \pi_{0,t-1}^*$)	**L**	**H**	**H-L**
β_1	-6.91	1.81	
$\mathbb{E}$(IIR)	1.96	1.74	-0.23
S.E.	0.04	0.03	0.03

f2 ($u_t - u_t^*$)	**L**	**H**	**H-L**
β_2	-2.70	3.73	
$\mathbb{E}$(IIR)	1.50	2.16	0.66
S.E.	0.04	0.03	0.04

f3 (w_t)	**L**	**H**	**H-L**
β_3	-0.88	0.63	
$\mathbb{E}$(IIR)	2.06	1.63	-0.43
S.E.	0.03	0.03	0.03

f4 (s_t)	**L**	**H**	**H-L**
β_4	-0.09	0.03	
$\mathbb{E}$(IIR)	2.00	1.68	-0.31
S.E.	0.03	0.03	0.03

f5 (pu_t)	**L**	**H**	**H-L**
β_5	-0.01	0.02	
$\mathbb{E}$(IIR)	1.50	2.18	0.68
S.E.	0.05	0.03	0.05

f6 ($nfci_t$)	**L**	**H**	**H-L**
β_6	-2.25	6.44	
$\mathbb{E}$(IIR)	1.70	1.98	0.29
S.E.	0.04	0.04	0.05

Table B3: **Fama-MacBeth Regressions for 6 Benchmark Factors (60-Month Rolling Window)**

This table presents the factor lambda estimates from Fama-MacBeth (1973) 2^{nd} stage cross-sectional regressions of the 6 benchmark factors (upper panel), and the annualized spread $\hat{E}\left[(\beta_{75^{th}f,t} - \beta_{25^{th}f,t})\lambda_{f,t}\right]$ between two hypothetical goods with different betas on the factor f, everything else being equal (lower panel). The first portfolio's beta is the 75th percentile, while that of the second is the 25th percentile of the cross-sectional distribution of individual betas on factor f. The actual factors are the ARMA(1,1) residuals of the corresponding factors, and the analysis is based on the 60-month rolling window. The description for the six benchmark factors is reported in Table 2. Columns **1** to **6** of this table report the univariate estimation for the corresponding factors, and columns **I** to **XVI** report the corresponding estimations for all the sixteen ($2^4 = 16$) possible multi-variate specifications while holding the two Phillips curve factors, $\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$ and $u_t - u_t^*$, fixed. Factor lambda estimations are displayed in percentage units and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

	1	**2**	**3**	**4**	**5**	**6**	**I**	**II**	**III**	**IV**	**V**
Intercept	1.64***	1.51***	1.50***	1.51***	1.46***	1.56***	1.57***	1.54***	1.53***	1.55***	1.56***
	(30.79)	(25.41)	(24.30)	(28.17)	(26.16)	(27.65)	(34.61)	(35.42)	(37.43)	(39.81)	(40.14)
1. $\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	−0.04***						−0.03**	−0.03**	−0.03***	−0.05***	−0.06***
	(−2.75)						(−2.24)	(−2.43)	(−2.35)	(−3.55)	(−4.30)
2. $u_t - u_t^*$		0.13***					0.17***	0.15***	0.15***	0.12***	0.11***
		(4.48)					(6.82)	(5.81)	(5.85)	(4.60)	(4.27)
3. w_t			−0.45***					−0.68***	−0.62***	−0.60***	−0.70***
			(−3.93)					(−3.62)	(−3.53)	(−3.94)	(−3.61)
4. s_t				−1.32*					−2.41***	−3.13***	−3.43***
				(−1.38)					(−2.96)	(−3.98)	(−4.12)
5. pu_t					17.42***					9.11***	10.62***
					(5.89)					(3.23)	(3.71)
6. $nfci_t$						0.01					0.04***
						(0.45)					(3.61)
R^2_{adj}	0.18	0.15	0.13	0.15	0.13	0.13	0.26	0.30	0.34	0.38	0.41
Economic magnitudes (in %) (IIR^{75th} − IIR^{25th} = 1.68%)											
$\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	−0.09						−0.08	−0.07	−0.08	−0.14	−0.18
$u_t - u_t^*$		0.26					0.39	0.31	0.30	0.26	0.19
w_t			−0.20					−0.15	−0.14	−0.16	−0.14
s_t				−0.17					−0.13	−0.20	−0.21
pu_t					0.45					0.18	0.20
$nfci_t$						0.08					0.26

Table B3: continued from previous page

	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV	XVI
Intercept	1.55^{***}	1.56^{***}	1.56^{***}	1.55^{***}	1.54^{***}	1.55^{***}	1.55^{***}	1.57^{***}	1.52^{***}	1.56^{***}	1.57^{***}
	(35.67)	(36.36)	(35.77)	(37.75)	(36.85)	(37.04)	(36.49)	(37.22)	(38.05)	(38.59)	(37.84)
1. $\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	-0.02^{**}	-0.06^{***}	-0.04^{***}	-0.06^{***}	-0.04^{***}	-0.05^{***}	-0.04^{***}	-0.07^{***}	-0.05^{***}	-0.07^{***}	-0.06^{***}
	(−1.85)	(−4.09)	(−3.08)	(−4.15)	(−3.23)	(−3.63)	(−3.02)	(−4.59)	(−3.49)	(−4.69)	(−4.44)
2. $u_t - u_t^*$	0.16^{***}	0.13^{***}	0.16^{***}	0.11^{***}	0.14^{***}	0.12^{***}	0.15^{***}	0.12^{***}	0.14^{***}	0.10^{***}	0.11^{***}
	(6.52)	(5.23)	(6.39)	(4.23)	(5.47)	(5.04)	(6.14)	(4.62)	(5.48)	(3.83)	(4.42)
3. w_t				-0.66^{***}	-0.58^{***}				-0.55^{***}	-0.56^{***}	
				(−3.77)	(−3.17)				(−3.40)	(−3.30)	
4. s_t	-2.22^{**}					-2.99^{***}	-2.72^{***}		-2.53^{***}		-3.46^{***}
	(−2.72)					(−3.80)	(−3.21)		(−2.95)		(−4.19)
5. pu_t		10.03^{***}		7.32^{***}		11.34^{***}		11.35^{***}		8.88^{***}	13.53^{***}
		(3.60)		(2.60)		(4.05)		(3.85)		(3.01)	(4.65)
6. $nfci_t$			0.03^{***}		0.04^{***}		0.03^{***}	0.03^{**}	0.05^{***}	0.04^{***}	0.03^{***}
			(2.53)		(3.32)		(2.60)	(2.37)	(3.87)	(3.18)	(2.57)
R^2_{adj}	0.30	0.30	0.30	0.35	0.34	0.34	0.34	0.34	0.38	0.38	0.37
Economic magnitudes (in %) ($\mathbf{IIR}^{75th} - \mathbf{IIR}^{25th} = 1.68\%$)											
$\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	−0.05	−0.20	−0.12	−0.18	−0.11	−0.15	−0.11	−0.22	−0.15	−0.21	−0.19
$u_t - u_t^*$	0.37	0.31	0.34	0.23	0.26	0.30	0.31	0.25	0.24	0.16	0.22
w_t				−0.15	−0.15				−0.14	−0.16	−0.22
s_t	−0.13					−0.19	−0.16		−0.14		
pu_t		0.18		0.14		0.22		0.20		0.16	0.24
$nfci_t$			0.21		0.26		0.21	0.17	0.30	0.23	0.18

Table B4: **Fama-MacBeth Regressions for 6 Benchmark Factors (120-Month Rolling Window)**

This table presents the factor lambda estimates from Fama-MacBeth (1973) 2^{nd} stage cross-sectional regressions of the 6 benchmark factors (upper panel), and the annualized spread $\hat{E}\left[(\beta_{75^{th}f,t} - \beta_{25^{th}f,t})\lambda_{f,t}\right]$ between two hypothetical goods with different betas on the factor f, everything else being equal (lower panel). The first portfolio's beta is the 75th percentile, while that of the second is the 25th percentile of the cross-sectional distribution of individual betas on factor f. The actual factors are the ARMA(1,1) residuals of the corresponding factors, and the analysis is based on the 120-month rolling window. The description for the six benchmark factors is reported in Table 2. Columns **1** to **6** of this table report the univariate estimation for the corresponding factors, and columns **I** to **XVI** report the corresponding estimations for all the sixteen ($2^4 = 16$) possible multi-variate specifications while holding the two Phillips curve factors, $\pi_t^{(\text{LTE})} - \pi^*_{0,t-1}$ and $u_t - u^*_t$, fixed. Factor lambda estimations are displayed in percentage units and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

	1′	**2′**	**3′**	**4′**	**5′**	**6′**	**I′**	**II′**	**III′**	**IV′**	**V′**
Intercept	1.45***	1.34***	1.42***	1.39***	1.37***	1.42***	1.34***	1.35***	1.33***	1.30***	1.29***
	(26.93)	(20.08)	(20.76)	(26.55)	(26.41)	(25.77)	(29.95)	(33.11)	(34.63)	(34.78)	(35.99)
1. $\pi_t^{(\text{LTE})} - \pi^*_{0,t-1}$	−0.06***						−0.07***	−0.07***	−0.05***	−0.09***	−0.09***
	(−4.01)						(−5.19)	(−5.25)	(−3.77)	(−5.66)	(−5.45)
2. $u_t - u^*_t$		0.19***					0.19***	0.17***	0.17***	0.16***	0.13***
		(9.83)					(11.74)	(9.57)	(9.14)	(8.71)	(6.88)
3. w_t			−0.54***					−0.28***	−0.32***	−0.25***	−0.23***
			(−7.28)					(−3.66)	(−4.20)	(−3.30)	(−3.15)
4. s_t				−5.16***					−4.13***	−3.29***	−2.97***
				(−4.84)					(−4.45)	(−3.81)	(−3.40)
5. pu_t					13.08***					14.52***	12.25***
					(3.98)					(4.44)	(3.91)
6. $nfci_t$						0.02*					0.10***
						(1.35)					(6.46)
R^2_{adj}	0.19	0.12	0.13	0.16	0.09	0.14	0.23	0.27	0.29	0.33	0.35
Economic magnitudes (in %) (IIR^{75th} − IIR^{25th} = 1.68%)											
$\pi_t^{(\text{LTE})} - \pi^*_{0,t-1}$	−0.12						−0.18	−0.19	−0.11	−0.26	−0.22
$u_t - u^*_t$		0.55					0.56	0.50	0.48	0.45	0.34
w_t			−0.35					−0.13	−0.13	−0.08	−0.07
s_t				−0.34					−0.20	−0.17	−0.15
pu_t					0.20					0.20	0.14
$nfci_t$						0.15					0.38

Table B4: continued from previous page

	VI′	VII′	VIII′	IX′	X′	XI′	XII′	XIII′	XIV′	XV′	XVI′
Intercept	1.32***	1.31***	1.30***	1.33***	1.32***	1.29***	1.29***	1.30***	1.30***	1.31***	1.28***
	(30.29)	(30.14)	(31.41)	(33.56)	(34.45)	(30.46)	(31.30)	(31.67)	(35.37)	(35.15)	(31.70)
1. $\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	−0.05***	−0.10***	−0.06***	−0.10***	−0.06***	−0.10***	−0.05***	−0.10***	−0.05***	−0.10***	−0.10***
	(−3.67)	(−6.02)	(−4.18)	(−6.01)	(−3.88)	(−6.05)	(−3.43)	(−6.03)	(−3.40)	(−5.83)	(−6.10)
2. $u_t - u_t^*$	0.17***	0.18***	0.15***	0.17***	0.12***	0.16***	0.13***	0.15***	0.11***	0.13***	0.13***
	(10.64)	(11.21)	(8.97)	(9.20)	(6.21)	(9.72)	(7.91)	(9.48)	(5.96)	(7.02)	(8.01)
3. w_t				−0.24***	−0.30***				−0.36***	−0.27***	
				(−3.19)	(−4.02)				(−4.86)	(−3.61)	
4. s_t	−3.11***					−2.65***	−2.37***		−2.65***		−2.56***
	(−3.49)					(−2.92)	(−2.51)		(−2.94)		(−2.81)
5. pu_t		7.05**		11.10***		12.36***		6.04**		9.46***	9.92***
		(2.06)		(3.28)		(3.73)		(1.87)		(3.00)	(3.12)
6. $nfci_t$			0.08***		0.09***		0.09***	0.06***	0.10***	0.08***	0.09***
			(5.28)		(6.20)		(6.35)	(4.40)	(7.04)	(5.60)	(5.97)
R^2_{adj}	0.26	0.27	0.26	0.31	0.30	0.29	0.29	0.29	0.32	0.33	0.32
Economic magnitudes (in %) (IIR^{75th} − IIR^{25th} = 1.68%)											
$\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	−0.12	−0.24	−0.12	−0.24	−0.09	−0.28	−0.10	−0.23	−0.09	−0.22	−0.26
$u_t - u_t^*$	0.51	0.51	0.42	0.46	0.34	0.45	0.37	0.42	0.30	0.35	0.35
w_t				−0.11	−0.14				−0.15	−0.12	−0.13
s_t	−0.19					−0.14	−0.14		−0.13		
pu_t		0.09		0.16		0.16		0.05		0.11	0.10
$nfci_t$			0.34		0.37		0.40	0.27	0.42	0.32	0.37

Table B5: **Robustness Check: Eight Pro-Cyclical Univariate Factors**

This table presents the factor lambda estimates from Fama-MacBeth (1973) 2^{nd} stage cross-sectional regressions of the eight pro-cyclical factors for additional robustness checks, the description of which is reported in Table 2. The actual factors are the ARMA(1,1) residuals of the corresponding factors. Panel A is based on the 60-month rolling window analysis. Panel B is based on the 120-month rolling window analysis. Factor lambda estimations are displayed in percentage units and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

		Panel A: 60-month window								**Panel B: 120-month window**							
8 factors	**corr(fr,gdp)**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**7′**	**8′**	**9′**	**10′**	**11′**	**12′**	**13′**	**14′**
Intercept		1.61^{***}	1.59^{***}	1.56^{***}	1.52^{***}	1.50^{***}	1.58^{***}	1.56^{***}	1.50^{***}	1.45^{***}	1.40^{***}	1.36^{***}	1.41^{***}	1.36^{***}	1.39^{***}	1.39^{***}	1.38^{***}
		(29.94)	(25.49)	(28.28)	(28.46)	(26.50)	(25.37)	(30.56)	(30.61)	(22.76)	(20.01)	(22.42)	(28.79)	(25.77)	(20.92)	(29.46)	(28.55)
7. $\pi_t^{(I)} - \pi_{0,t}$	0.14	−0.22								−0.10							
		(−0.98)								(−0.32)							
8. $\pi_t^{(O)} - \pi_{0,t}$	0.18		-5.89^{***}								-2.89^{**}						
			(−4.12)								(−1.83)						
9. ind_t	0.27			-0.64^{***}								-0.69^{***}					
				(−5.51)								(−6.80)					
10. ipc_t	0.23				-0.74^{***}								-0.78^{***}				
					(−5.74)								(−7.10)				
11. ipd_t	0.23					-1.09^{***}								-1.92^{***}			
						(−3.08)								(−6.77)			
12. inc_t	0.10						0.09								-0.78^{***}		
							(0.54)								(−4.07)		
13. cg_t	0.25							-0.14^{**}								-0.60^{***}	
								(−2.12)								(−7.22)	
14. bbk_t	0.21								-19.88^{***}								-20.57^{***}
									(−5.10)								(−6.10)
R^2_{adj}		0.14	0.14	0.16	0.12	0.12	0.09	0.10	0.16	0.12	0.07	0.08	0.07	0.08	0.08	0.08	0.11

Table B6: **Robustness Check: Six Counter-Cyclical Univariate Factors**

This table presents the factor lambda estimates from Fama-MacBeth (1973) 2^{nd} stage cross-sectional regressions of the six counter-cyclical factors for additional robustness checks, the description of which is reported in Table 2. The actual factors are the ARMA(1,1) residuals of the corresponding factors. Panel A is based on the 60-month rolling window analysis. Panel B is based on the 120-month rolling window analysis. Factor lambda estimations are displayed in percentage units and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

		Panel A: 60-month window						**Panel B: 120-month window**					
6 factors	**corr(fr,gdp)**	**15**	**16**	**17**	**18**	**19**	**20**	**15′**	**16′**	**17′**	**18′**	**19′**	**20′**
Intercept		1.53***	1.52***	1.54***	1.47***	1.56***	1.51***	1.43***	1.44***	1.46***	1.41***	1.46***	1.42***
		(28.63)	(28.03)	(27.24)	(26.50)	(29.08)	(28.13)	(27.01)	(26.12)	(26.31)	(28.07)	(27.44)	(27.88)
15. cat_t	−0.17	26.02***						13.95***					
		(5.06)						(2.51)					
16. $eput_t$	−0.14		31.20***						28.98***				
			(4.68)						(4.00)				
17. $epum_t$	−0.08			41.65***						16.73*			
				(3.73)						(1.33)			
18. cbs_t	−0.26				0.04*						0.04*		
					(1.42)						(1.32)		
19. cs_t	−0.20					−0.03						0.05	
						(−0.71)						(1.12)	
20. ebp_t	−0.19						0.01						0.03
							(0.36)						(0.87)
R^2_{adj}		0.13	0.13	0.16	0.15	0.16	0.16	0.10	0.11	0.12	0.11	0.14	0.13

Table B7: **Robustness Check: Three Alternatives to Financial Condition Factor,** $nfci$

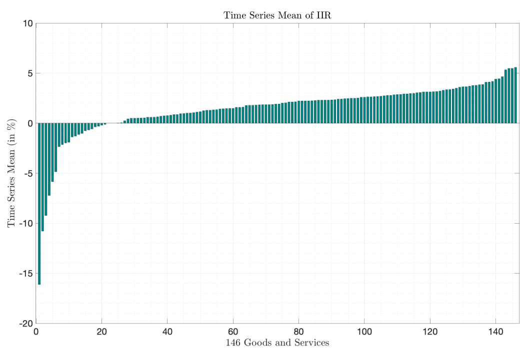
This table presents the factor lambda estimates from Fama-MacBeth (1973) 2^{nd} stage cross-sectional regressions of the 3 alternatives, *cbs*, *cs* and *ebp*, to the financial condition factor $nfci_t$ in the benchmark model, for additional robustness checks, the description of which is reported in Table 2. The actual factors are the ARMA(1,1) residuals of the corresponding factors. Panel A is based on 60-month rolling window analysis. Panel B is based on 120-month rolling window analysis. Factor lambda estimations are displayed in percentage units and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

	Panel A: 60-month window			**Panel B: 120-month window**		
	cbs	**cs**	**ebp**	**cbs**	**cs**	**ebp**
$Intercept$	1.58^{***}	1.58^{***}	1.58^{***}	1.34^{***}	1.34^{***}	1.33^{***}
	(42.13)	(40.15)	(41.81)	(36.73)	(36.99)	(36.02)
$\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^{*}$	-0.03^{**}	-0.03^{**}	-0.02^{*}	-0.09^{***}	-0.07^{***}	-0.06^{***}
	(-1.94)	(-1.84)	(-1.53)	(-5.75)	(-4.09)	(-3.54)
$u_t - u_t^{*}$	0.11^{***}	0.13^{***}	0.11^{***}	0.15^{***}	0.16^{***}	0.15^{***}
	(4.65)	(5.26)	(4.43)	(8.07)	(8.47)	(8.03)
w_t	-0.72^{***}	-0.61^{***}	-0.76^{***}	-0.26^{***}	-0.25^{***}	-0.21^{***}
	(-4.46)	(-3.64)	(-4.42)	(-3.75)	(-3.49)	(-2.91)
s_t	-2.63^{***}	-2.47^{***}	-2.51^{***}	-3.92^{***}	-3.36^{***}	-3.52^{***}
	(-3.37)	(-3.06)	(-3.25)	(-4.69)	(-4.07)	(-4.37)
pu_t	7.43^{***}	8.38^{***}	6.45^{***}	17.93^{***}	14.98^{***}	13.61^{***}
	(2.52)	(3.11)	(2.49)	(5.48)	(4.90)	(4.68)
fc_t	0.08^{***}	0.12^{***}	0.10^{***}	-0.02	0.09^{**}	0.08^{**}
	(2.91)	(3.92)	(2.90)	(-0.61)	(2.39)	(2.25)
R^2_{adj}	0.42	0.42	0.42	0.35	0.35	0.35

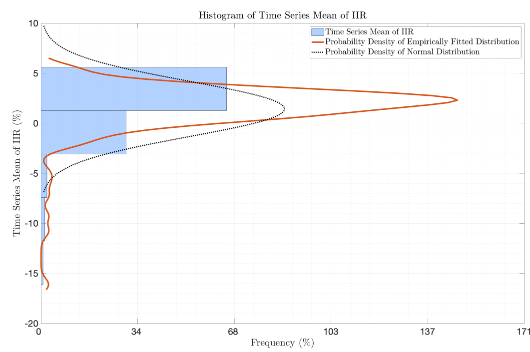
Table B8: **Link to Inflation Risk and Risk Premium (60-Month Rolling Window)**

This table presents the results of the regression of changes in the inflation risk premium proxies on the beta changes corresponding to the six benchmark factors. Dependent variables are two proxies: **BEIR**, which is the log change of 10-year breakeven inflation, and **BondMkt**, which is the change of rolling window beta from regressing the log price change of the 10-Year Treasury Bond on the log index change of S&P500. Independent variables are the changes in median $\Delta\beta_t^{50th}$ and changes in "interquartile" $\Delta(\beta_t^{80th} - \beta_t^{20th})$ of the corresponding actual factors. The analysis is based on the 60-month rolling window. Estimations are displayed in percentage units and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annualized monthly data, the sample period of **BEIR** is from January 2003 to December 2019, and the sample period of **BondMkt** is from January 1990 to December 2019.

Factor	**Regressor**	**BEIR**	**BondMkt**
	$Intercept$	0.00	-0.15^{***}
		(-6.02)	(-5.74)
$\pi_t^{(\text{LTE})} - \pi_{0,t-1}^*$	$\Delta\beta_{\pi,t}^{50th}$	0.06^{***}	-1.91^{***}
		(6.03)	(-11.73)
$u_t - u_t^*$	$\Delta\beta_{u,t}^{50th}$	-0.08^{***}	-0.36
		(-5.35)	(-3.78)
w_t	$\Delta\beta_{w,t}^{50th}$	-0.29	5.01
		(-15.99)	(7.06)
s_t	$\Delta\beta_{s,t}^{50th}$	2.11^{***}	10.56^{***}
		(5.75)	(2.25)
pu_t	$\Delta\beta_{pu,t}^{50th}$	-4.62^{***}	-55.02^{***}
		(-6.56)	(-4.01)
$nfci_t$	$\Delta\beta_{fc,t}^{50th}$	-0.03^{***}	0.52^{***}
		(-4.32)	(7.48)
$\pi_t^{(\text{LTE})} - \pi_{0,t-1}^*$	$\Delta\left(\beta_{\pi,t}^{80th} - \beta_{\pi,t}^{20th}\right)$	0.01^{**}	-0.16^{***}
		(3.32)	(-3.25)
$u_t - u_t^*$	$\Delta\left(\beta_{u,t}^{80th} - \beta_{u,t}^{20th}\right)$	0.04^{***}	-0.38^{***}
		(11.13)	(-7.59)
w_t	$\Delta\left(\beta_{w,t}^{80th} - \beta_{w,t}^{20th}\right)$	-0.06^{***}	3.31^{***}
		(-5.51)	(11.56)
s_t	$\Delta\left(\beta_{s,t}^{80th} - \beta_{s,t}^{20th}\right)$	3.69^{***}	-10.67^{***}
		(15.68)	(-5.18)
pu_t	$\Delta\left(\beta_{pu,t}^{80th} - \beta_{pu,t}^{20th}\right)$	-1.11^{***}	22.27^{***}
		(-3.34)	(3.61)
$nfci_t$	$\Delta\left(\beta_{fc,t}^{80th} - \beta_{fc,t}^{20th}\right)$	0.01^{***}	0.03^{***}
		(6.53)	(1.32)
R_{adj}^2		0.09	0.16

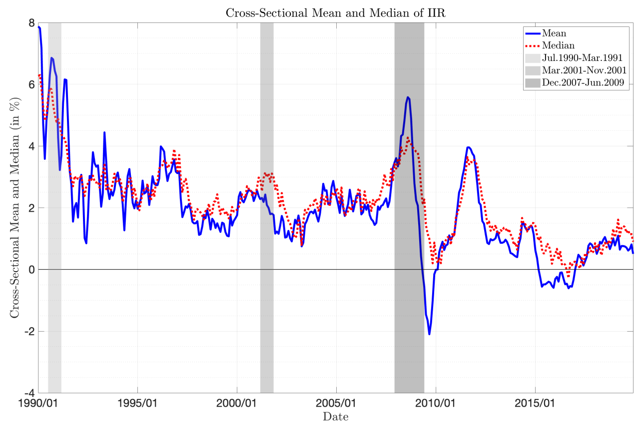


(a) Sorted Time Series Mean of IIR

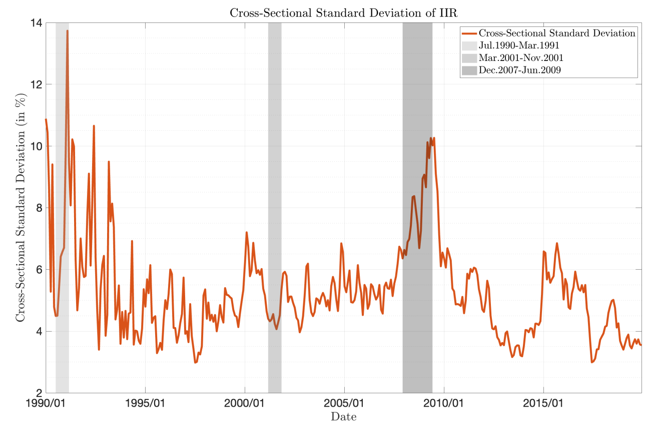


(b) Time Series Mean of IIR Histogram

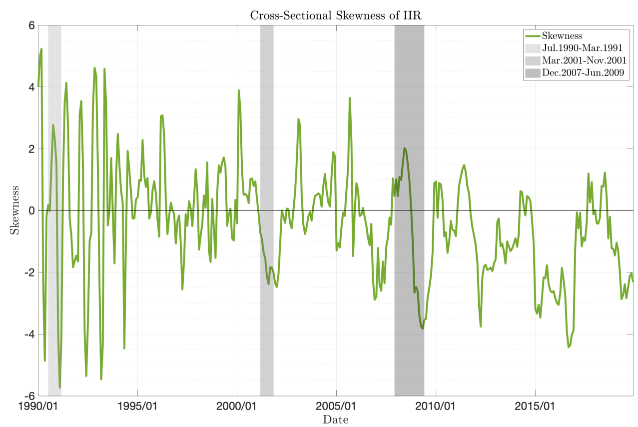
Figure B1: **Time Series Mean of Individual Inflation Rate (IIR)**
The 146 categories of goods and services are reported in Table 1 in the paper. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.



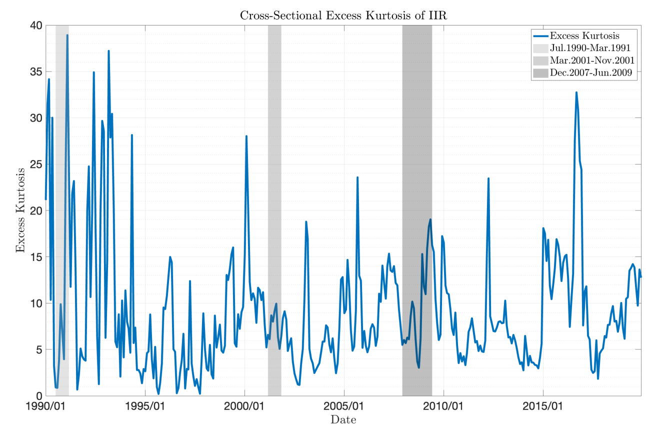
(a) Cross-Sectional Mean and Median of IIR



(b) Cross-Sectional Standard Deviation of IIR



(c) Cross-Sectional Skewness of IIR



(d) Cross-Sectional Excess Kurtosis of IIR

Figure B2: **Time Series Plots of Cross-Sectional Moments of Individual Inflation Rate (IIR)**
The 146 categories of goods and services are reported in Table 1 in the paper. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

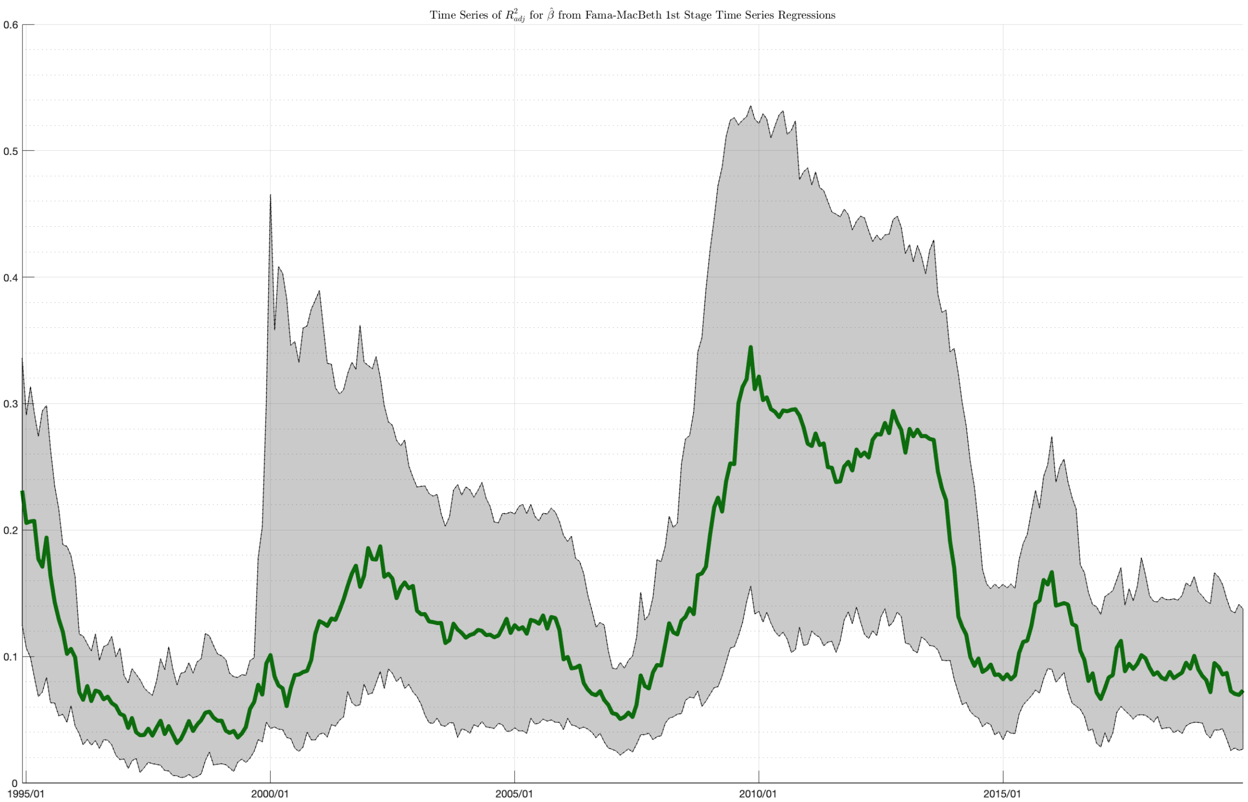


Figure B3: **Time Series Plot of Goodness of Fit (R^2_{adj}) from Time Series Regressions**
The plot of R^2_{adj} (across 146 goods and services) is the median of the adjusted goodness of fit from Fama-MacBeth (1973) 1^{st} stage time-series regressions of model **V** (based on the 60-month rolling window), with shaded 1st and 5th quintile confidence bound.

Appendix C Analysis of IEIR on 142 Goods and Services

From Figure 1 in the paper, we see there are approximate four categories of goods that have significantly more extensive IEIR than others, so in this section, we remove the four goods with the most extreme negative IEIR from our sample and present a similar cross-sectional analysis of IEIR based on the remaining 142 goods and services (out of the 146 categories in the paper). The sample period is the same from January 1990 to December 2019.

Panel A of Figure C1 plots the sample averages of the 142 IEIR time series that we analyze in the section, as well as their histogram; Panel (a) shows that the sorted times-series mean of the 142 IEIR is more even than that of the 146 IEIR, the minimum and maximum average IEIR among the 142 goods and services are -7.60% and 3.36%, respectively. Panel (b) illustrates that the fitted probability density function (pdf) is much closer to the pdf of normal distribution than that of the 146 IEIR shown in Figure 1 in the paper. The figure illustrates well the considerable variation of these values in the cross-section of the 142 IEIR.

We follow a similar procedure as in the paper; Table C2 presents the descriptive statistics of the 142 IEIR series. A typical good price now grows annually at 0.25% less than the general inflation rate (which is 0.50% based on 146 IEIR). The 5th percentile averages -6.94% while the 95th percentile averages 6.35% through time, a difference of 13.29% (for 146 IEIR, the difference is 14.14%), and these 5th and 95th percentiles are still very large compared to the median IEIR that averages to -0.17% through time (for 146 IEIR, it is -0.24%), illustrating that an IEIR of a consumer good is likely to be more extreme than normal, and this is again confirmed by the large IEIR cross-sectional excess kurtosis that averages 9.44 through time (for 146 IEIR, it is 9.24).

In Figure C2, we plot the time series patterns of the cross-sectional moments of the IEIR and highlight the NBER recessions. These cross-sectional moments show substantial time-series variations, as confirmed by the IEIR descriptive statistics in Table C2.

Based on the six benchmark factors selected in the paper, the two-group univariate beta sorting results shown in Table C3, and FM cross-section regression results through the 60-month and 120-

month rolling windows shown in Table C4 and Table C5, respectively, shows the similar results in general that pro-cyclical factors: long-term inflation expectations, wages, and consumer sentiment have significant and robust negative factor lambdas, while counter-cyclical factors: unemployment, economic policy uncertainty have significant and robust positive factor lambdas, regardless of the model specification, besides for the factor of financial conditions, it changes signs in the two-group beta sorting exercise and no longer significant based on the 60-month rolling window analysis, but when extend the window to 120-month, the factor lambda of financial condition is still positive, significant and robust no matter the model specifications, which is consistent with the results of 146 IEIR and confirm our theory again. In conclusion, the findings are robust and stronger when using a longer rolling window of 120 months in estimating the conditional betas. Also, the economic magnitudes are considerable compared to the reference point of 0.69%.

Further robustness checks of eight pro-cyclical factors shown in Table C6 and six counter-cyclical factors shown in Table C7 reconfirm the findings based on 146 IEIR, no matter the analysis is based on the 60-month rolling window or 120-month window. However, the univariate factor lambdas for the three alternatives of financial conditions: corporate bond spread, credit spread, and excess bond premium, are not significant, but when we consider them in the six-factor model, besides *cs* based on the 60-month rolling window analysis, is positive and significant as shown in Table C8.

Table C9 reports the regression results of changes in our inflation risk and risk premium proxies on changes in the median beta corresponding to each economic factor. In general, the estimation on $\beta_{50^{th},t}$ is consistent with the results from IEIR, but the estimation on slopes turned negative besides consumer sentiment and financial conditions.

Figure C3 shows a very similar pattern to that in Figure 4 of the paper: the average explanatory power is the highest (a median adjusted goodness of fit, R^2_{adj}, between 42% and 54% across 142 consumer goods) during the period corresponding to the four rounds of quantitative easing (QE) lanched by the FED to fight against the financial crisis.

So the cross-sectional analysis based on 142 IEIR is highly consistent with that on 146 IEIR.

Table C1: **142 Goods and Services**

This table reports the 142 categories of goods and services included in the analysis. The last four goods marked with strikethrough in the table are excluded from the 146 categories in the original study since these four goods have the most extreme negative values that may affect the conclusion. We assume that the goods and services on the list are purchased for consumption rather than in pursuit of returns, which include non-durables and durables, because non-durables are short-lived, consumed rapidly, and unlikely to hold long enough to be resold until prices increase; durables may last longer, but due to wear and tear, as well as possible product upgrades on the market, these durables are usually purchased with the intent to consume rather than hold and resell for profit. The 142 goods and services in this table are sorted (ranking shown in column #) by their corresponding individual excess inflation rate (IEIR) in descending order. IEIR are in percentage units. Data were downloaded from the U.S. Bureau of Labor Statistics (BLS) on 17 November 2021.

#	Goods and Services	IEIR	#	Goods and Services	IEIR
1	Hospital services	3.36	***36***	Salt and other seasonings and spices	0.67
2	Delivery services	3.20	***37***	Food at employee sites and schools	0.65
3	College tuition and fees	3.18	***38***	Rent of primary residence	0.63
4	Elementary and high school tuition and fees	3.06	***39***	Admission to movies, theaters, and concerts	0.61
5	Veterinarian services	2.36	***40***	Laundry and dry cleaning services	0.58
6	Water and sewerage maintenance	2.24	***41***	Motor vehicle repair	0.58
7	Technical and business school tuition and fees	2.04	***42***	Other lodging away from home including hotels and motels	0.57
8	Housing at school, excluding board	1.99	***43***	Fresh biscuits, rolls, muffins	0.57
9	Cigarettes	1.88	***44***	Tomatoes	0.56
10	Fuel oil and other fuels	1.70	***45***	Other fresh vegetables	0.52
11	Motor vehicle insurance	1.69	***46***	Apples	0.52
12	Nursing homes and adult day services	1.67	***47***	Full service meals and snacks	0.49
13	Day care and preschool	1.60	***48***	Owners' equivalent rent of primary residence	0.46
14	Postage	1.55	***49***	Potatoes	0.46
15	Dental services	1.49	***50***	Moving, storage, freight expense	0.38
16	Admission to sporting events	1.46	***51***	Other condiments	0.29
17	Prescription drugs	1.45	***52***	Bacon, breakfast sausage, and related products	0.28
18	Garbage and trash collection	1.36	***53***	Frankfurters	0.24
19	Legal services	1.31	***54***	Other fats and oils including peanut butter	0.22
20	Funeral expenses	1.29	***55***	Fruits and vegetables	0.18
21	Cable and satellite television service	1.28	***56***	Pet food	0.17
22	Citrus fruits	1.23	***57***	Cakes, cupcakes, and cookies	0.11
23	Butter and margarine	1.07	***58***	Canned fruits and vegetables	0.09
24	Fresh fish and seafood	1.03	***59***	Services by other medical professionals	0.05
25	Fees for lessons or instructions	1.00	***60***	Cereals and bakery products	0.04
26	Other food away from home	1.00	***61***	Sauces and gravies	0.03
27	Pet services	0.93	***62***	Meats, poultry, fish, and eggs	-0.01
28	Parking and other fees	0.92	***63***	Rice, pasta, cornmeal	-0.01
29	Food at elementary and secondary schools	0.87	***64***	Other bakery products	-0.06
30	Gasoline (all types)	0.80	***65***	Airline fares	-0.08
31	Bread	0.77	***66***	Snacks	-0.11
32	Alcoholic beverages away from home	0.75	***67***	Processed fruits and vegetables	-0.12
33	Beef and veal	0.74	***68***	Flour and prepared flour mixes	-0.17
34	Physicians' services	0.71	***69***	Cheese and related products	-0.19
35	Financial services	0.70	***70***	Coffee	-0.26

Table C1: **continued from previous page**

#	Goods and Services	IEIR	#	Goods and Services	IEIR
71	Soups	-0.26	***109***	Miscellaneous household products	-1.40
72	Dairy and related products	-0.29	***110***	Tires	-1.41
73	Energy services	-0.29	***111***	Frozen and freeze dried prepared foods	-1.47
74	Poultry	-0.30	***112***	Sewing machines, fabric and supplies	-1.55
75	Intercity train fare	-0.34	***113***	Watches	-1.60
76	Processed fish and seafood	-0.35	***114***	Jewelry	-1.60
77	Lettuce	-0.36	***115***	Stationery, stationery supplies, gift wrap	-1.67
78	Other uncooked poultry including turkey	-0.37	***116***	New vehicles	-1.72
79	Sugar and sweets	-0.37	***117***	Household cleaning products	-1.75
80	Ice cream and related products	-0.39	***118***	Internet services and electronic information providers	-1.76
81	Lunchmeats	-0.46	***119***	Music instruments and accessories	-1.78
82	Other dairy and related products	-0.46	***120***	Men's footwear	-1.90
83	Other food at home	-0.50	***121***	Fresh milk other than whole	-1.91
84	Frozen fruits and vegetables	-0.53	***122***	Used cars and trucks	-1.92
85	Fresh whole milk	-0.54	***123***	Women's footwear	-1.98
86	Ham	-0.56	***124***	Women's underwear, nightwear, swimwear and accessories	-2.09
87	Club membership for shopping clubs, fraternal, or other organizations, or participant sports fees	-0.56	***125***	Infants' and toddlers' apparel	-2.41
88	Alcoholic beverages at home	-0.56	***126***	Men's pants and shorts	-2.42
89	Eggs	-0.60	***127***	Women's outerwear	-2.53
90	Whiskey at home	-0.70	***128***	Women's dresses	-2.61
91	Eyeglasses and eye care	-0.79	***129***	Outdoor equipment and supplies	-2.66
92	Other fresh fruits	-0.84	***130***	Nonelectric cookware and tableware	-2.74
93	Other pork including roasts, steaks, and ribs	-0.89	***131***	Men's suits, sport coats, and outerwear	-2.78
94	Carbonated drinks	-0.92	***132***	Leased cars and trucks	-2.83
95	Pork chops	-0.97	***133***	Major appliances	-2.85
96	Nonalcoholic beverages and beverage materials	-0.98	***134***	Ship fare	-3.20
97	Salad dressing	-0.99	***135***	Men's shirts and sweaters	-3.43
98	Bananas	-1.07	***136***	Women's suits and separates	-3.53
99	Car and truck rental	-1.08	***137***	Sports equipment	-3.70
100	Sports vehicles including bicycles	-1.16	***138***	Other furniture	-4.05
101	Distilled spirits, excluding whiskey, at home	-1.17	***139***	Other appliances	-4.12
102	Other beverage materials including tea	-1.18	***140***	Window coverings	-4.40
103	Other motor fuels	-1.23	***141***	Toys, games, hobbies and playground equipment	-6.42
104	Nonfrozen noncarbonated juices and drinks	-1.23	***142***	Audio equipment	-7.60
105	Purchase of pets, pet supplies, accessories	-1.31	*143*	~~Photographic equipment~~	-9.24
106	Breakfast cereal	-1.35	*144*	~~Computers, peripherals, and smart home assistants~~	-11.15
107	Boys' and girls' footwear	-1.39	*145*	~~Other video equipment~~	-12.93
108	Men's underwear, nightwear, swimwear and accessories	-1.40	*146*	~~Televisions~~	-18.23

Table C2: **Descriptive Statistics of Individual Excess Inflation Rate (IEIR)**

This table presents the mean, standard deviation (Std.Dev.), skewness (Skew.), excess kurtosis (Kurt.) and the real per capita GDP growth correlations of the cross-sectional mean, standard deviation (Std.Dev.), skewness (Skew.), excess kurtosis (Kurt.), and 5%, 25%, 50%(median), 75% and 95% percentiles among the 142 individual excess inflation rate (IEIR), which is constructed as $\pi^e_{i,t} \equiv \ln\left(\frac{P_{i,t}/P_{0,t}}{P_{i,t-1}/P_{0,t-1}}\right)$ (See Equation (2) for other equivalent forms). The 142 individual price indices are downloaded from the U.S. Bureau of Labor Statistics (BLS), displayed in Table C1. The mean, standard deviation, and percentiles are in percentage units. The 142 IEIR are annualized monthly data, and the sample period is from January 1990 to December 2019.

	Mean	**Std.Dev.**	**Skew.**	**Kurt.**	**5%**	**25%**	**50%**	**75%**	**95%**
Mean	−0.25	4.92	0.15	9.44	−6.94	−2.29	−0.17	1.73	6.35
Std.Dev.	0.87	1.66	2.05	8.31	1.90	0.91	1.01	1.06	2.71
Skew.	0.65	1.67	−0.42	1.49	−2.01	0.76	1.18	1.21	1.63
Kurt.	2.24	3.76	0.20	2.15	6.36	3.18	4.17	3.87	3.23
corr(π^e, gdp)	−0.25	−0.26	0.13	−0.06	0.11	−0.16	−0.19	−0.32	−0.39

Table C3: **Univariate Beta Sorting**

This table presents the univariate beta sorting results based on the six benchmark factors, the description for which is reported in Table 2. Individual consumer goods and services are sorted into two baskets (H, L) by the corresponding medians of the six univariate beta on the Individual Excess Inflation Rate (IEIR). Panel A is based on the 60-month rolling window analysis. Panel B is based on the 120-month rolling window analysis. Actual factors are the ARMA(1,1) residuals of the corresponding original factors. Average IEIR ($\mathbb{E}(\pi_i)$) and standard errors (S.E.) are in percentage units. All factors are annualized monthly data, and the sample period is from January 1990 to December 2019.

Panel A: 60-Month Window

f1 ($\pi_t^{\mathbf{LTE}} - \pi_{0,t-1}^*$)	**L**	**H**	**H-L**
β_1	-3.93	4.87	
$\mathbb{E}(\pi^e)$	-0.26	-0.15	0.11
S.E.	0.03	0.02	0.03

f2 ($u_t - u_t^*$)	**L**	**H**	**H-L**
β_2	-2.21	2.99	
$\mathbb{E}(\pi^e)$	-0.29	-0.12	0.16
S.E.	0.03	0.02	0.03

f3 (w_t)	**L**	**H**	**H-L**
β_3	-0.85	0.48	
$\mathbb{E}(\pi^e)$	-0.13	-0.27	-0.14
S.E.	0.02	0.02	0.03

f4 (s_t)	**L**	**H**	**H-L**
β_4	-0.05	0.07	
$\mathbb{E}(\pi^e)$	-0.18	-0.22	-0.04
S.E.	0.03	0.02	0.03

f5 (pu_t)	**L**	**H**	**H-L**
β_5	-0.02	0.02	
$\mathbb{E}(\pi^e)$	-0.35	-0.06	0.29
S.E.	0.02	0.03	0.03

f6 ($nfci_t$)	**L**	**H**	**H-L**
β_6	-4.59	5.63	
$\mathbb{E}(\pi^e)$	-0.13	-0.27	-0.14
S.E.	0.03	0.03	0.04

Panel B: 120-Month Window

f1 ($\pi_t^{\mathbf{LTE}} - \pi_{0,t-1}^*$)	**L**	**H**	**H-L**
β_1	-3.58	4.72	
$\mathbb{E}(\pi^e)$	-0.12	-0.23	-0.10
S.E.	0.02	0.01	0.03

f2 ($u_t - u_t^*$)	**L**	**H**	**H-L**
β_2	-1.83	3.43	
$\mathbb{E}(r)$	-0.25	-0.11	0.14
S.E.	0.02	0.01	0.03

f3 (w_t)	**L**	**H**	**H-L**
β_3	-0.89	0.33	
$\mathbb{E}(\pi^e)$	-0.20	-0.13	0.07
S.E.	0.02	0.02	0.03

f4 (s_t)	**L**	**H**	**H-L**
β_4	-0.04	0.06	
$\mathbb{E}(\pi^e)$	-0.07	-0.26	-0.19
S.E.	0.02	0.01	0.02

f5 (pu_t)	**L**	**H**	**H-L**
β_5	-0.01	0.01	
$\mathbb{E}(\pi^e)$	-0.21	-0.13	0.08
S.E.	0.02	0.02	0.03

f6 ($nfci_t$)	**L**	**H**	**H-L**
β_6	-3.01	3.79	
$\mathbb{E}(\pi^e)$	-0.18	-0.17	0.01
S.E.	0.01	0.02	0.03

Table C4: **Fama-MacBeth Regressions for 6 Benchmark Factors (60-Month Rolling Window)**

This table presents the factor lambda estimates from Fama-MacBeth (1973) 2^{nd} stage cross-sectional regressions of the 6 benchmark factors (upper panel), and the annualized spread $\hat{E}\left[(\beta_{75^{th}f,t} - \beta_{25^{th}f,t})\lambda_{f,t}\right]$ between two hypothetical goods with different betas on the factor f, everything else being equal (lower panel). The first portfolio's beta is the 75th percentile, while that of the second is the 25th percentile of the cross-sectional distribution of individual betas on factor f. The actual factors are the ARMA(1,1) residuals of the corresponding original factors, and the analysis is based on the 60-month rolling window. The description for the six benchmark factors is reported in Table 2. Columns **1** to **6** of this table report the univariate estimation for the corresponding factors, and columns **I** to **XVI** report the corresponding estimations for all the sixteen ($2^4 = 16$) possible multi-variate specifications while holding the two Phillips curve factors, $\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$ and $u_t - u_t^*$, fixed. Factor lambda estimations are displayed in percentage units and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

	1	**2**	**3**	**4**	**5**	**6**	**I**	**II**	**III**	**IV**	**V**
Intercept	-0.20^{***}	-0.33^{***}	-0.35^{***}	-0.26^{***}	-0.30^{***}	-0.29^{***}	-0.26^{***}	-0.28^{***}	-0.28^{***}	-0.30^{***}	-0.28^{***}
	(-4.86)	(-7.93)	(-8.87)	(-6.08)	(-6.60)	(-6.93)	(-7.79)	(-8.90)	(-9.60)	(-11.25)	(-11.02)
1. $\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	-0.03^{**}						-0.01	-0.01	-0.02	-0.02^{*}	-0.03^{**}
	(-2.30)						(-0.93)	(-1.12)	(-1.23)	(-1.53)	(-2.21)
2. $u_t - u_t^*$		0.08^{***}					0.09^{***}	0.08^{***}	0.09^{***}	0.06^{***}	0.07^{***}
		(2.70)					(3.89)	(3.31)	(3.50)	(2.44)	(2.91)
3. w_t			-0.34^{***}					-0.55^{***}	-0.49^{***}	-0.59^{***}	-0.47^{***}
			(-2.94)					(-2.91)	(-2.74)	(-3.25)	(-2.78)
4. s_t				-0.82					-2.13^{***}	-3.02^{***}	-3.23^{***}
				(-0.84)					(-2.51)	(-3.72)	(-3.83)
5. pu_t					12.97^{***}					3.77^{*}	4.43^{*}
					(4.29)					(1.35)	(1.57)
6. $nfci_t$						0.00					0.00
						(-0.18)					(-0.18)
R^2_{adj}	0.21	0.17	0.15	0.17	0.14	0.14	0.29	0.35	0.39	0.44	0.48
Economic magnitudes (in %) ($\mathbf{IEIR}^{75th} - \mathbf{IEIR}^{25th} = 0.69\%$)											
$\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	-0.06						0.00	0.02	0.00	0.00	-0.03
$u_t - u_t^*$		0.15					0.20	0.14	0.13	0.12	0.12
w_t			-0.11					-0.07	-0.05	-0.06	-0.04
s_t				-0.12					-0.11	-0.18	-0.19
pu_t					0.33					0.10	0.11
$nfci_t$						0.03					0.12

Table C4: continued from previous page

	VI	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**	**XIII**	**XIV**	**XV**	**XVI**
Intercept	-0.27^{***}	-0.28^{***}	-0.27^{***}	-0.30^{***}	-0.28^{***}	-0.29^{***}	-0.28^{***}	-0.27^{***}	-0.28^{***}	-0.28^{***}	-0.28^{***}
	(-8.59)	(-9.45)	(-8.46)	(-10.57)	(-9.59)	(-10.02)	(-9.22)	(-9.47)	(-10.38)	(-10.49)	(-9.88)
1. $\pi_t^{(\mathrm{LTE})} - \pi^*_{0,t-1}$	-0.01	-0.03^{**}	-0.03^{**}	-0.03^{**}	-0.03^{**}	-0.03^{**}	-0.03^{**}	-0.04^{***}	-0.03^{**}	-0.03^{**}	-0.04^{***}
	(-1.02)	(-2.04)	(-1.82)	(-2.00)	(-1.77)	(-2.01)	(-1.92)	(-2.48)	(-2.10)	(-2.37)	(-2.58)
2. $u_t - u_t^*$	0.09^{***}	0.06^{***}	0.10^{***}	0.05^{**}	0.10^{***}	0.06^{**}	0.10^{***}	0.06^{***}	0.10^{***}	0.06^{***}	0.06^{**}
	(3.66)	(2.50)	(4.16)	(2.05)	(3.82)	(2.28)	(3.94)	(2.58)	(4.05)	(2.45)	(2.33)
3. w_t				-0.56^{***}	-0.44^{**}				-0.40^{***}	-0.43^{***}	
				(-3.10)	(-2.36)				(-2.44)	(-2.45)	
4. s_t	-1.50^{**}					-2.41^{***}	-2.20^{***}		-2.44^{***}		-2.76^{***}
	(-1.81)					(-3.05)	(-2.59)		(-2.77)		(-3.36)
5. pu_t		6.07^{**}		2.45		7.48^{***}		5.73^{**}		2.94	8.02^{***}
		(2.21)		(0.87)		(2.72)		(1.93)		(0.99)	(2.77)
6. $nfci_t$			-0.01		0.00		-0.01	-0.02	0.00	-0.01	-0.02
			(-0.62)		(-0.17)		(-0.99)	(-1.13)	(0.17)	(-0.64)	(-1.25)
R^2_{adj}	0.34	0.35	0.34	0.40	0.39	0.39	0.39	0.39	0.44	0.44	0.43
Economic magnitudes (in %) (IEIR^{75th} − IEIR^{25th} = 0.69%)											
$\pi_t^{(\mathrm{LTE})} - \pi^*_{0,t-1}$	0.01	-0.07	-0.04	-0.04	-0.01	-0.04	-0.03	-0.09	-0.04	-0.05	-0.07
$u_t - u_t^*$	0.17	0.13	0.23	0.08	0.18	0.12	0.20	0.14	0.17	0.10	0.10
w_t				-0.08	-0.05				-0.03	-0.06	-0.16
s_t	-0.08					-0.15	-0.13		-0.13		
pu_t		0.11		0.06		0.16		0.11		0.07	0.16
$nfci_t$			0.05		0.10		0.04	0.01	0.13	0.07	0.02

Table C5: **Fama-MacBeth Regressions for 6 Benchmark Factors (120-Month Rolling Window)**

This table presents the factor lambda estimates from Fama-MacBeth (1973) 2^{nd} stage cross-sectional regressions of the 6 benchmark factors (upper panel), and the annualized spread $\hat{E}\big[(\beta_{75^{th}f,t} - \beta_{25^{th}f,t})\lambda_{f,t}\big]$ between two hypothetical goods with different betas on the factor f, everything else being equal (lower panel). The first portfolio's beta is the 75th percentile, while that of the second is the 25th percentile of the cross-sectional distribution of individual betas on factor f. The actual factors are the ARMA(1,1) residuals of the corresponding original factors, and the analysis is based on the 120-month rolling window. The description for the six benchmark factors is reported in Table 2. Columns **1** to **6** of this table report the univariate estimation for the corresponding factors, and columns **I** to **XVI** report the corresponding estimations for all the sixteen ($2^4 = 16$) possible multi-variate specifications while holding the two Phillips curve factors, $\pi_t^{(\mathrm{LTE})} - \pi^*_{0,t-1}$ and $u_t - u^*_t$, fixed. Factor lambda estimations are displayed in percentage units and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

	1′	**2′**	**3′**	**4′**	**5′**	**6′**	**I′**	**II′**	**III′**	**IV′**	**V′**
Intercept	-0.29^{***}	-0.41^{***}	-0.41^{***}	-0.29^{***}	-0.28^{***}	-0.37^{***}	-0.29^{***}	-0.31^{***}	-0.30^{***}	-0.31^{***}	-0.32^{***}
	(−6.17)	(−9.45)	(−9.15)	(−6.03)	(−5.84)	(−7.74)	(−8.40)	(−10.16)	(−9.99)	(−10.83)	(−11.33)
1. $\pi_t^{(\mathrm{LTE})} - \pi^*_{0,t-1}$	-0.05^{***}						-0.04^{***}	-0.05^{***}	-0.04^{***}	-0.05^{***}	-0.05^{***}
	(−3.19)						(−3.15)	(−3.52)	(−2.56)	(−3.24)	(−3.10)
2. $u_t - u^*_t$		0.10^{***}					0.07^{***}	0.05^{***}	0.06^{***}	0.06^{***}	0.04^{***}
		(5.33)					(4.69)	(2.87)	(3.02)	(3.17)	(1.94)
3. w_t			-0.26^{***}					-0.13^{***}	-0.11^{***}	-0.10^{***}	-0.06^{***}
			(−3.76)					(−1.78)	(−1.15)	(−1.46)	(−0.94)
4. s_t				-3.64^{***}					-3.30^{***}	-3.31^{***}	-2.88^{***}
				(−3.41)					(−3.49)	(−3.71)	(−3.28)
5. pu_t					4.12^{***}					6.42^{***}	4.76^{***}
					(1.21)					(2.12)	(1.63)
6. $nfci_t$						0.01^{*}					0.03^{***}
						(0.33)					(2.22)
R^2_{adj}	0.22	0.13	0.14	0.18	0.10	0.15	0.26	0.31	0.34	0.37	0.39
Economic magnitudes (in %) (IEIR^{75th} − IEIR^{25th} = 0.69%)											
$\pi_t^{(\mathrm{LTE})} - \pi^*_{0,t-1}$	−0.10						−0.09	−0.11	−0.07	−0.14	−0.10
$u_t - u^*_t$		0.31					0.20	0.13	0.14	0.14	0.08
w_t			−0.19					−0.11	−0.08	−0.06	−0.03
s_t				−0.23					−0.15	−0.15	−0.13
pu_t					0.00					0.07	0.05
$nfci_t$						0.07					0.15

Table C5: continued from previous page

	VI′	VII′	VIII′	IX′	X′	XI′	XII′	XIII′	XIV′	XV′	XVI′
Intercept	-0.28^{***}	-0.30^{***}	-0.30^{***}	-0.33^{***}	-0.32^{***}	-0.29^{***}	-0.28^{***}	-0.31^{***}	-0.30^{***}	-0.33^{***}	-0.29^{***}
	(-8.30)	(-9.06)	(-8.54)	(-10.89)	(-10.50)	(-8.96)	(-8.36)	(-9.65)	(-10.51)	(-11.47)	(-9.25)
1. $\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	-0.04^{***}	-0.06^{***}	-0.04^{***}	-0.06^{***}	-0.04^{***}	-0.06^{***}	-0.03^{**}	-0.06^{***}	-0.03^{**}	-0.06^{***}	-0.06^{***}
	(-2.66)	(-3.52)	(-2.66)	(-3.87)	(-2.60)	(-3.54)	(-2.20)	(-3.72)	(-1.99)	(-3.67)	(-3.65)
2. $u_t - u_t^*$	0.06^{***}	0.07^{***}	0.05^{***}	0.05^{***}	0.02	0.06^{***}	0.04^{**}	0.06^{***}	0.02	0.03^{**}	0.04^{***}
	(4.06)	(5.02)	(3.14)	(2.94)	(1.25)	(4.06)	(2.26)	(3.70)	(1.10)	(1.70)	(2.61)
3. w_t				-0.15^{**}	-0.12^{*}				-0.14^{**}	-0.12^{*}	
				(-2.05)	(-1.58)				(-1.94)	(-1.74)	
4. s_t	-2.18^{**}					-2.32^{***}	-1.87^{**}		-2.56^{***}		-2.17^{***}
	(-2.27)					(-2.58)	(-2.03)		(-2.87)		(-2.42)
5. pu_t		3.80^{*}		4.18^{*}		6.88^{**}		2.22		2.65	5.29^{**}
		(1.19)		(1.35)		(2.19)		(0.73)		(0.91)	(1.75)
6. $nfci_t$			0.03^{**}		0.03^{**}		0.04^{**}	0.02	0.04^{***}	0.03^{**}	0.03^{**}
			(1.83)		(2.12)		(2.36)	(1.16)	(2.69)	(1.77)	(1.98)
R^2_{adj}	0.30	0.30	0.30	0.34	0.34	0.33	0.33	0.33	0.37	0.37	0.36
Economic magnitudes (in %) (IEIR^{75th} − IEIR^{25th} = 0.69%)											
$\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	-0.08	-0.11	-0.03	-0.14	-0.03	-0.15	-0.03	-0.11	-0.03	-0.11	-0.13
$u_t - u_t^*$	0.18	0.20	0.14	0.13	0.06	0.17	0.10	0.15	0.03	0.08	0.11
w_t				-0.10	-0.09				-0.08	-0.09	-0.10
s_t	-0.10					-0.11	-0.10		-0.12		
pu_t		0.04		0.04		0.08		0.01		0.02	0.06
$nfci_t$			0.16		0.16		0.18	0.10	0.19	0.13	0.15

Table C6: **Robustness Check: Eight Pro-Cyclical Univariate Factors**

This table presents the factor lambda estimates from Fama-MacBeth (1973) 2^{nd} stage cross-sectional regressions of the eight pro-cyclical factors for additional robustness checks, the description of which is reported in Table 2. The actual factors are the ARMA(1,1) residuals of the corresponding original factors. Panel A is based on the 60-month rolling window analysis. Panel B is based on the 120-month rolling window analysis. Factor lambda estimations are displayed in percentage units and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

		Panel A: 60-month window								**Panel B: 120-month window**							
8 factors	**corr(fr,gdp)**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**7′**	**8′**	**9′**	**10′**	**11′**	**12′**	**13′**	**14′**
Intercept		-0.32^{***}	-0.32^{***}	-0.33^{***}	-0.29^{***}	-0.36^{***}	-0.31^{***}	-0.27^{***}	-0.32^{***}	-0.42^{***}	-0.42^{***}	-0.32^{***}	-0.28^{***}	-0.32^{***}	-0.36^{***}	-0.25^{***}	-0.35^{***}
		(-8.71)	(-9.56)	(-10.19)	(-8.10)	(-10.35)	(-7.28)	(-6.30)	(-8.31)	(-9.37)	(-10.83)	(-8.81)	(-6.69)	(-8.67)	(-7.83)	(-5.41)	(-7.13)
7. $\pi_t^{(I)} - \pi_{0,t}$	0.14	-0.08								0.00							
		(-0.37)								(0.00)							
8. $\pi_t^{(O)} - \pi_{0,t}$	0.18		-4.60^{***}								-1.77						
			(-3.22)								(-1.14)						
9. ind_t	0.27			-0.62^{***}								-0.54^{***}					
				(-5.32)								(-5.37)					
10. ipc_t	0.23				-0.59^{***}								-0.45^{***}				
					(-4.58)								(-4.27)				
11. ipd_t	0.23					-1.12^{***}								-1.42^{***}			
						(-3.15)								(-5.14)			
12. inc_t	0.10						0.23^{*}								-0.37^{**}		
							(1.40)								(-1.91)		
13. cg_t	0.25							-0.05								-0.35^{***}	
								(-0.78)								(-4.29)	
14. bbk_t	0.21								-17.66^{***}								-13.36^{***}
									(-4.59)								(-3.97)
R^2_{adj}		0.16	0.15	0.18	0.12	0.14	0.11	0.11	0.17	0.14	0.08	0.08	0.07	0.08	0.09	0.10	0.13

Table C7: **Robustness Check: Six Counter-Cyclical Univariate Factors**

This table presents the factor lambda estimates from Fama-MacBeth (1973) 2^{nd} stage cross-sectional regressions of the six counter-cyclical factors for additional robustness checks, the description of which is reported in Table 2. The actual factors are the ARMA(1,1) residuals of the corresponding original factors. Panel A is based on the 60-month rolling window analysis. Panel B is based on the 120-month rolling window analysis. Factor lambda estimations are displayed in percentage units and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

		Panel A: 60-month window						**Panel B: 120-month window**					
6 factors	**corr(fr,gdp)**	**15**	**16**	**17**	**18**	**19**	**20**	**15′**	**16′**	**17′**	**18′**	**19′**	**20′**
Intercept		−0.26***	−0.25***	−0.27***	−0.30***	−0.25***	−0.28***	−0.30***	−0.30***	−0.37***	−0.35***	−0.34***	−0.35***
		(−5.90)	(−5.91)	(−6.47)	(−7.20)	(−5.92)	(−6.62)	(−6.05)	(−6.10)	(−8.17)	(−7.43)	(−7.09)	(−7.44)
15. cat_t	−0.17	19.21***						3.63					
		(3.69)						(0.64)					
16. $eput_t$	−0.14		19.40***						6.05				
			(2.89)						(0.81)				
17. $epum_t$	−0.08			33.81***						3.13			
				(2.99)						(0.25)			
18. cbs_t	−0.26				0.03						0.02		
					(1.04)						(0.63)		
19. cs_t	−0.20					−0.04						0.00	
						(−1.16)						(0.09)	
20. ebp_t	−0.19						0.00						0.01
							(0.01)						(0.14)
R^2_{adj}		0.14	0.14	0.18	0.16	0.17	0.17	0.11	0.13	0.14	0.12	0.16	0.15

Table C8: **Robustness Check: Three Alternatives to Financial Condition Factor,** $nfci$

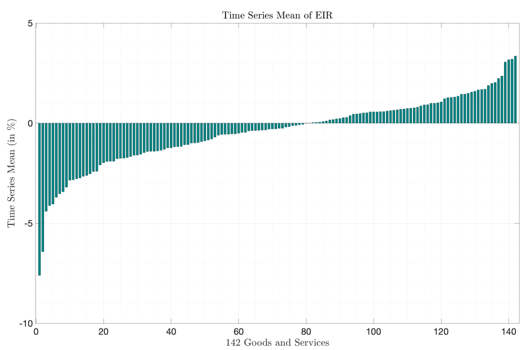
This table presents the factor lambda estimates from Fama-MacBeth (1973) 2^{nd} stage cross-sectional regressions of the 3 alternatives, *cbs*, *cs* and *ebp*, to the financial condition factor $nfci_t$ in the benchmark model, for additional robustness checks, the description of which is reported in Table 2. The actual factors are the ARMA(1,1) residuals of the corresponding original factors. Panel A is based on 60-month rolling window analysis. Panel B is based on 120-month rolling window analysis. Factor lambda estimations are displayed in percentage units and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

	Panel A: 60-month window			**Panel B: 120-month window**		
	cbs	**cs**	**ebp**	**cbs**	**cs**	**ebp**
$Intercept$	-0.28^{***}	-0.25^{***}	-0.27^{***}	-0.29^{***}	-0.29^{***}	-0.29^{***}
	(-11.88)	(-9.50)	(-10.84)	(-10.23)	(-9.96)	(-9.85)
$\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^{*}$	-0.02	-0.01	-0.01	-0.05^{***}	-0.03^{**}	-0.02
	(-1.22)	(-0.45)	(-0.54)	(-3.07)	(-2.02)	(-1.28)
$u_t - u_t^{*}$	0.05^{**}	0.07^{***}	0.05^{**}	0.04^{**}	0.05^{***}	0.05^{***}
	(2.14)	(3.06)	(2.18)	(2.21)	(2.70)	(2.76)
w_t	-0.61^{***}	-0.48^{***}	-0.66^{***}	-0.10^{*}	-0.13^{**}	-0.08
	(-3.77)	(-2.77)	(-3.73)	(-1.61)	(-1.98)	(-1.16)
s_t	-2.23^{***}	-2.60^{***}	-2.27^{***}	-3.58^{***}	-3.11^{***}	-3.01^{***}
	(-2.83)	(-3.15)	(-2.90)	(-4.18)	(-3.61)	(-3.62)
pu_t	1.37	3.52	0.93	7.35^{***}	8.39^{***}	6.59^{***}
	(0.47)	(1.30)	(0.36)	(2.51)	(3.00)	(2.51)
fc_t	0.02	0.06^{**}	0.03	-0.03	0.01	0.04
	(0.89)	(1.79)	(0.77)	(-0.84)	(0.16)	(1.01)
R^2_{adj}	0.48	0.48	0.49	0.40	0.40	0.40

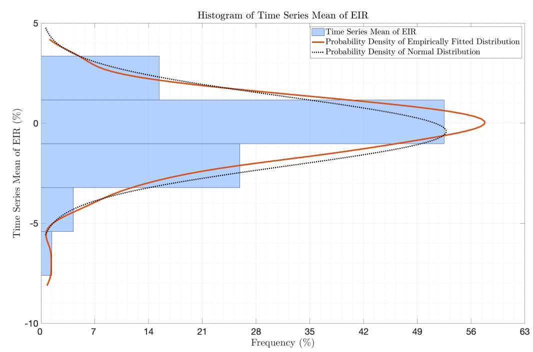
Table C9: **Link to Inflation Risk and Risk Premium (60-Month Rolling Window)**

This table presents the results of the regression of changes in the inflation risk premium proxies on the beta changes corresponding to the six benchmark factors. Dependent variables are two proxies: **BIEIR**, which is the log change of 10-year breakeven inflation, and **BondMkt**, which is the change of rolling window beta from regressing the log price change of the 10-Year Treasury Bond on the log index change of S&P500. Independent variables are the changes in median $\Delta\beta_t^{50th}$ and changes in "interquartile" $\Delta(\beta_t^{80th} - \beta_t^{20th})$ of the corresponding actual factors. The analysis is based on the 60-month rolling window. Estimations are displayed in percentage units and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annualized monthly data, the sample period of **BIEIR** is from January 2003 to December 2019, and the sample period of **BondMkt** is from January 1990 to December 2019.

Factor	**Regressor**	**BIEIR**	**BondMkt**
	$Intercept$	0.00^{*}	-0.17^{***}
		(-1.64)	(-7.37)
$\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	$\Delta\beta_{\pi,t}^{50th}$	0.06^{***}	-0.40^{***}
		(8.90)	(-4.54)
$u_t - u_t^*$	$\Delta\beta_{u,t}^{50th}$	-0.04^{***}	0.07
		(-3.93)	(0.67)
w_t	$\Delta\beta_{w,t}^{50th}$	0.09^{**}	-0.80^{**}
		(1.96)	(-2.33)
s_t	$\Delta\beta_{s,t}^{50th}$	3.37^{***}	-50.79^{***}
		(4.36)	(-11.17)
pu_t	$\Delta\beta_{pu,t}^{50th}$	-5.82^{***}	130.50^{***}
		(-5.08)	(7.83)
$nfci_t$	$\Delta\beta_{fc,t}^{50th}$	-0.05^{***}	-0.09^{***}
		(-6.35)	(-2.51)
$\pi_t^{(\mathrm{LTE})} - \pi_{0,t-1}^*$	$\Delta\left(\beta_{\pi,t}^{80th} - \beta_{\pi,t}^{20th}\right)$	0.00	0.30^{***}
		(-0.17)	(7.60)
$u_t - u_t^*$	$\Delta\left(\beta_{u,t}^{80th} - \beta_{u,t}^{20th}\right)$	-0.01^{***}	-0.30^{***}
		(-5.03)	(-6.19)
w_t	$\Delta\left(\beta_{w,t}^{80th} - \beta_{w,t}^{20th}\right)$	-0.01	0.68^{***}
		(-0.68)	(5.07)
s_t	$\Delta\left(\beta_{s,t}^{80th} - \beta_{s,t}^{20th}\right)$	3.90^{***}	-8.24^{***}
		(24.51)	(-5.71)
pu_t	$\Delta\left(\beta_{pu,t}^{80th} - \beta_{pu,t}^{20th}\right)$	-5.41^{***}	0.68
		(-12.60)	(0.10)
$nfci_t$	$\Delta\left(\beta_{fc,t}^{80th} - \beta_{fc,t}^{20th}\right)$	0.00^{**}	0.17^{***}
		(1.68)	(6.39)
R^2_{adj}		0.21	0.15

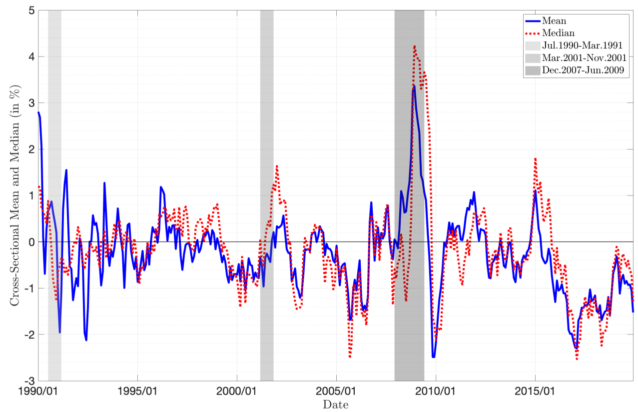


(a) Sorted Time Series Mean of IEIR

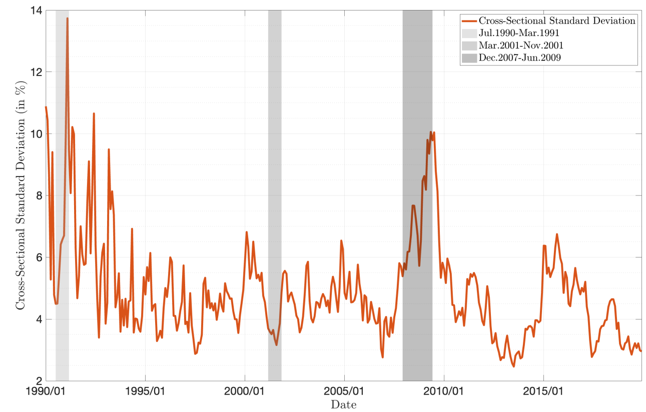


(b) Time Series Mean of IEIR Histogram

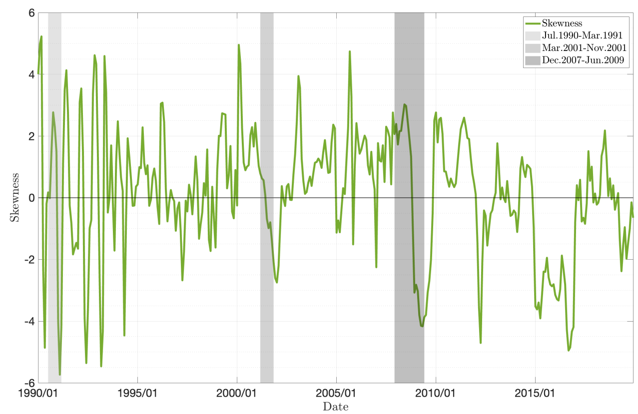
Figure C1: **Time Series Mean of Individual Excess Inflation Rate (IEIR)**
The 142 categories of goods and services are reported in Table C1. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.



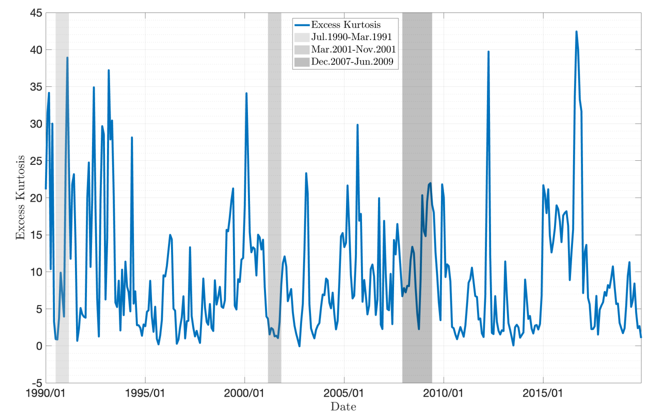
(a) Cross-Sectional Mean and Median of IEIR



(b) Cross-Sectional Standard Deviation of IEIR



(c) Cross-Sectional Skewness of IEIR



(d) Cross-Sectional Excess Kurtosis of IEIR

Figure C2: **Time Series Plots of Cross-Sectional Moments of Individual Excess Inflation Rate (IEIR)** The 142 categories of goods and services are reported in Table C1. Data are annualized monthly data, and the sample period is from January 1990 to December 2019.

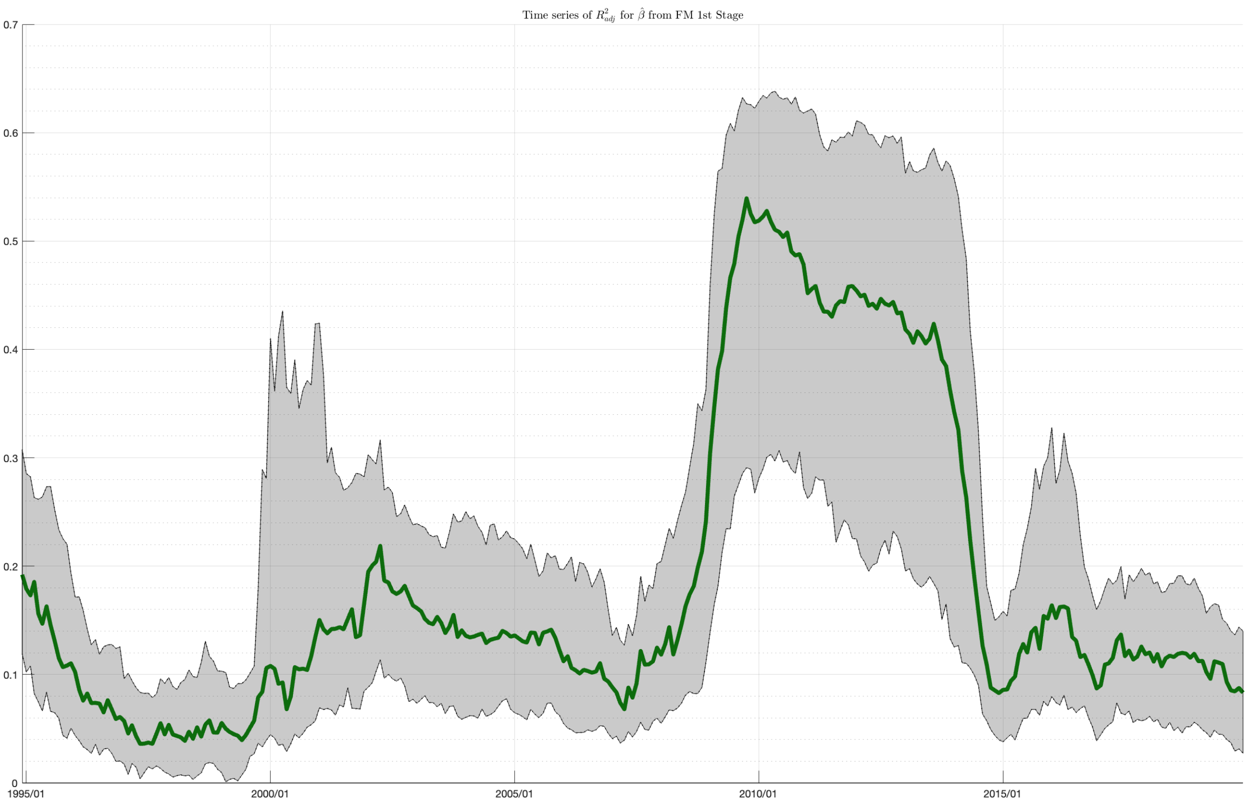


Figure C3: **Time Series Plot of Goodness of Fit (R^2_{adj}) from Time Series Regressions**
The plot of R^2_{adj} (across 142 goods and services) is the median of the adjusted goodness of fit from Fama-MacBeth (1973) 1^{st} stage time-series regressions of model **V** (based on the 60-month rolling window), with shaded 1st and 5th quintile confidence bound.

Appendix D Tests on Financial Asset Returns

In this section, we conduct a similar analysis on investment assets based on the six-benchmark factors; according to the cross-sectional asset pricing theory, in rational factor asset pricing models, the discrepancy in risk premia across different assets should be linked to a corresponding dispersion of sensitivities (factor loadings, or betas) to common risk factors. In most cases, these factors capture business cycle movements well. The main findings suggest that investors demand higher returns on average for assets whose returns tend to move more procyclical than other assets, which implies that the factor price (lambda) for pro-cyclical factors should be positive and for counter-cyclical factors should be negative. It has the opposite implication for the factor lambdas on consumer goods.

We test the returns of six portfolios: 49, 48, 38, 30, 17, and 12 industry portfolios on our six benchmark factors. The monthly data of return on the six industry portfolios are from Kenneth R. French's online data library. The dependent variables are annualized real returns of the corresponding six industry portfolios. The sample period is the same, from January 1990 to December 2019.

Table D1 presents the descriptive statistics of the real annualized returns on the 49 Industry Portfolios. A typical asset return grows annually at 9.26%, (for 146 IEIR, it is −0.5% of IEIR) and the 5th percentile averages −17.16% (for 146 IEIR, it is −7.86%) while the 95th percentile averages 39.45% (for 146 IEIR, it is 6.28% of IEIR) through time, a difference of 56.61% (for 146 IEIR, the difference is 14.14%), and these 5th and 95th percentiles are very large compared to the median IEIR that averages to 8.36% (for 146 IEIR, it is −0.24%) through time, illustrating that an IIR of a consumer good is likely to be much more extreme than normal (much more extreme than IEIR), and this is confirmed by the large cross-sectional standard deviation that averages 17.58% (for 146 IEIR, it is 5.31%) through time.

Figure D1 shows considerable heterogeneity of factor loadings (betas) among the 49 industry portfolios; the interesting finding is that for the three counter-cyclical factors: unemployment gap, economic policy uncertainty, and financial conditions, factor loadings are almost all negative, and factor loading on pro-cyclical factors: wage and consumer sentiment are mostly positive while it is more like evenly distributed on long-term inflation expectation.

Although we expected the opposite factor lambdas on investment assets, and despite the theoretical importance of macroeconomic risk factors in explaining the cross-section of expected asset returns, empirical evidence on the existence of risk premia on macro-factors is mixed and not robust to the different econometric methodologies used. As summarized by Li (2016) that one of the most influential papers is by Chen et al. (1986), who finds exposures to five macroeconomic factors, including industrial production growth, the change in expected inflation, unexpected inflation, the yield spread between a long-term and a short-term government bond, and the yield spread between low credit rating and high credit rating bonds are priced in the cross-section of stock returns. Shanken and Weinstein (2006), however, find that the results of Chen et al. (1986) are not robust to alternative test assets and the way the betas are estimated. Macro factor-based asset pricing models also fail to explain certain cross-sectional stock return anomalies such as momentum (Griffin et al. (2003)) and profitability premium (Wang and Yu (2013)). Most studies commonly attribute the empirical failure of the macro factor-based asset pricing model to the large measurement errors in macroeconomic factors, the difference between a theoretical definition and its empirical counterpart, or the low frequency in reporting macroeconomic variables.

Hong and Sraer (2016) argue that the speculative nature of high beta stocks offsets the risk-sharing effect, leading to the high beta-low return puzzle.

Most macro-factors models are not successful in explaining cross-sectional risk premia, with the conditional CAPM offering the highest fit, alternative multifactor models, based on the interest rate and bond yield factors, outperform the macro models, factors related to asset prices seem to provide better information for equity risk premia than “pure” macro variables.

Table D2 shows the estimated factor prices (lambdas) based on the 60-month rolling window, from which we could see that the estimate of factor price for pro-cyclical factors: long-term inflation expectation is positive and significant on the 17 industry portfolios and wages is positive and significant on the 12 industry portfolios, but consumer sentiment is still negative and significant in all six portfolios; for counter-cyclical factors: unemployment gap turned to negative and significant on 49, 48 and 38 industry portfolios, policy uncertainty are negative and significant in all six industry portfolios; and financial condition turn to negative and significant on 30, 17, 12 industry portfolios. These results, in general, verify the risk-return tradeoff theory that pro-cyclical factors have positive factor prices while counter-cyclical factors have negative factor prices.

Table D1: **Descriptive Statistics of Real Excess Annual Return of 49 Industry Portfolios**

This table reports the time-series mean, standard deviation (Std.Dev.), skewness (Skew.), excess kurtosis (Kurt.) and the real per capita GDP growth correlations of the cross-sectional mean, standard deviation (Std.Dev.), skewness (Skew.), excess kurtosis (Kurt.), and 5%, 25%, 50%(median), 75% and 95% percentiles among the real excess annual return of 49 Industry Portfolios. The mean, standard deviation and percentiles are in percentage units. The sample period is from January 1990 to December 2019.

	Mean	**Std.Dev.**	**Skew.**	**Kurt.**	**5%**	**25%**	**50%**	**75%**	**95%**
Mean	9.26	17.58	0.35	2.16	−17.16	−0.96	8.36	18.39	39.45
Std.Dev.	15.22	5.70	1.03	3.63	16.30	15.20	15.07	15.90	22.04
Skew.	−0.36	1.50	0.82	4.56	−0.59	−0.63	−0.20	−0.02	0.49
Kurt.	2.22	2.49	2.91	31.50	0.61	1.35	2.13	2.72	2.33
corr(gdp)	0.44	−0.03	0.06	0.00	0.46	0.44	0.42	0.42	−0.32

Table D2: **Industry Portfolios (60-month window)**

This table presents the factor lambda estimation from Fama-MacBeth (1973) 2^{nd} stage cross-sectional regressions. The dependent variables are annulized real returns of the corresponding six industry portfolios from Kenneth R. French online data library. The actual factors are the ARMA(1,1) residuals of the corresponding factors and the analysis is based on 60-month rolling window. Factor lambda estimations are displayed (in %) and t-statistics are shown in parentheses. *, **, and *** indicate statistical significance of the factor lambdas at the 90%, 95%, and 99% levels respectively. Data are annulized monthly data, the sample period is from January 1990 to December 2019.

	P49	**P48**	**P38**	**P30**	**P17**	**P12**
$Intercept$	6.32^{***}	6.33^{***}	6.46^{***}	6.26^{***}	4.46^{***}	5.27^{***}
	(12.10)	(12.12)	(10.75)	(11.50)	(7.38)	(7.80)
$\pi_t^{(\text{LTE})} - \pi^*_{0.t-1}$	-0.02	-0.02	-0.01	-0.03	0.04^{*}	-0.05
	(-1.02)	(-1.15)	(-0.48)	(-1.41)	(1.57)	(-1.42)
$u_t - u_t^*$	-0.07^{**}	-0.08^{**}	-0.06^{*}	0.02	-0.03	-0.03
	(-2.06)	(-2.43)	(-1.65)	(0.64)	(-0.67)	(-0.52)
w_t	0.21	0.32	-0.25	0.11	0.44	1.04^{**}
	(0.74)	(1.10)	(-1.23)	(0.28)	(1.60)	(2.01)
s_t	-4.87^{***}	-4.88^{***}	-7.09^{***}	-4.33^{***}	-1.90	-0.73
	(-4.48)	(-4.45)	(-5.98)	(-3.62)	(-1.48)	(-0.35)
pu_t	-10.95^{***}	-10.99^{***}	-12.82^{***}	-11.80^{***}	-8.27^{*}	-34.80^{***}
	(-3.37)	(-3.39)	(-3.39)	(-2.98)	(-1.55)	(-4.67)
$nfci_t$	-0.02	-0.02	-0.04	-0.05^{**}	-0.08^{***}	-0.09^{***}
	(-1.08)	(-1.09)	(-1.40)	(-1.97)	(-2.61)	(-3.51)
R^2_{adj}	0.55	0.56	0.57	0.63	0.72	0.79

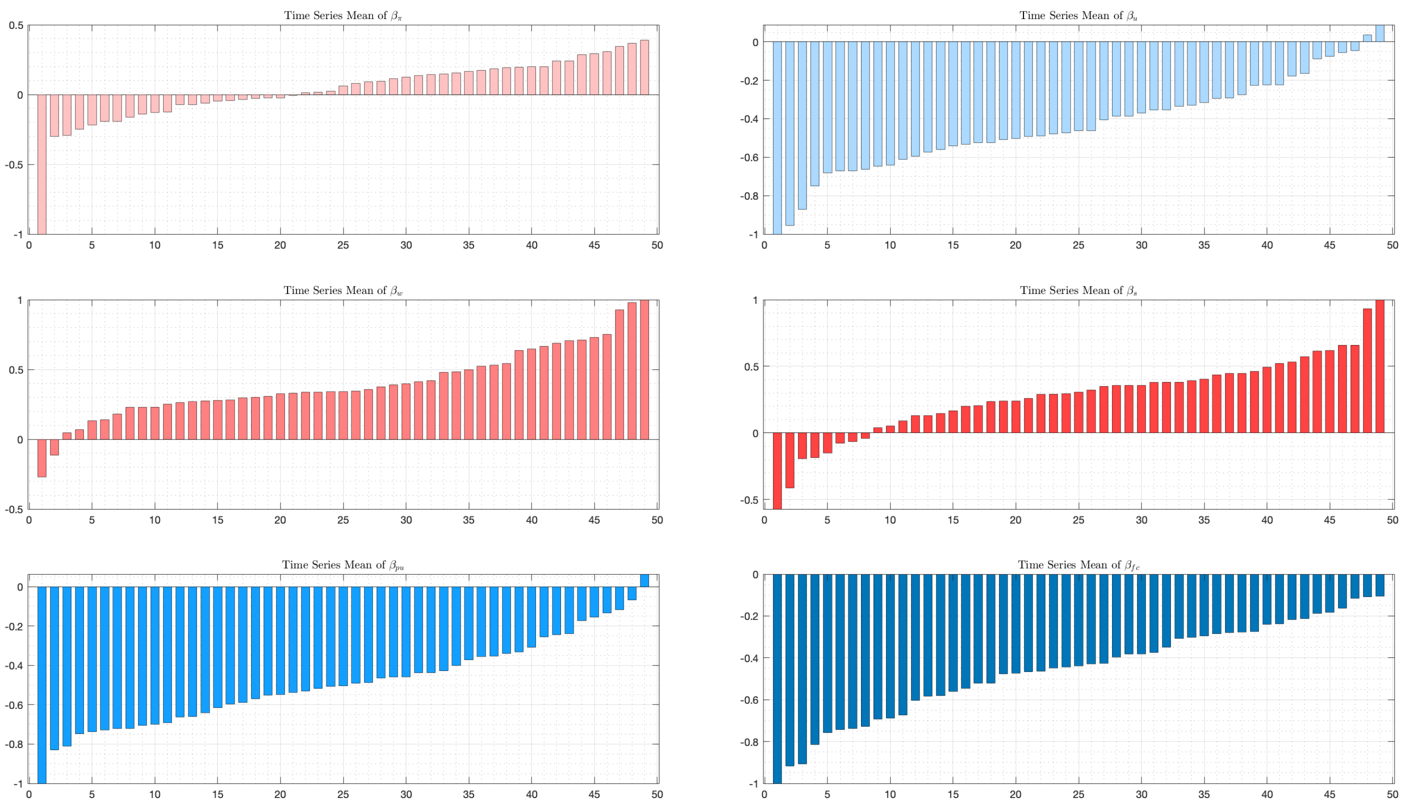


Figure D1. Time Series of Univariate Beta (Based on 60-month Window)

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