The Relative Price Premium

January 2024

Abstract

This study shows that relative price dispersion impacts risk premia. Notably, firms associated with goods and services that have increased (decreased) in price relative to the headline inflation rate earn high (low) returns. We refer to this return spread of 0.88% per month as the relative price premium. We rationalize the premium via a consumption-based asset-pricing model that features imperfectly substitutable goods and an investor with preferences for the mix of goods consumed. As shocks to relative prices induce the investor to consume a suboptimal bundle of goods, high price dispersion signals bad times for the investor and the economy.

The central tenant underlying most economic theories is that agents are better off when they consume more rather than less. Building on this basic assumption, the consumption-based asset-pricing paradigm pioneered by Lucas (1978) and Breeden (1979) features the growth rate of aggregate consumption as the sole determinant of an investor's wellbeing. While most investors are undoubtedly concerned about *how much* they consume, intuition suggests that agents also care about the *types* of goods and services they are consuming. Despite this intuition, most asset-pricing models are silent about the composition of the representative investor's consumption. Are investors indeed worse off when they consume the same amount but different types of goods and services? If so, can we quantify the risks associated with shocks to the composition of an investor's consumption? We address these questions both empirically and theoretically.

In this paper we study how dispersion in the prices of consumer goods and services impacts the asset prices of the firms that provide these goods. Specifically, we show that firms that have recently experienced the greatest increases (decreases) in the price of their output earn an average stock return of 1.14% (0.26%) per month, resulting in a spread of 0.88% per month that we refer to as the *relative price premium*. For instance, if food prices increase more than the price of medical care, then food-related firms tend to earn a higher risk premium than medical care providers. This premium cannot be explained by differences in markups, market power, or price rigidity between firms associated with goods and services that have increased and decreased in price. As such, we consider a consumption-based explanation for why the relative price premium arises.

We rationalize this result in the context of an endowment economy with multiple imperfectly substitutable goods and a representative investor who faces uncertainty about how much of each good will be available in each period. Our economic setting features two key ingredients: (1) a shock to the level of aggregate consumption; and (2) a reallocative shock that governs how much of each good is available to consume. While the first ingredient is quite standard, as negative shocks to aggregate consumption are bad for consumers, the second ingredient is more novel to our setting.

On the theoretical front we show why price dispersion is priced. When a reallocative shock hits the economy, the price of the more available (scarce) goods tends to fall (rise). Hence, goods prices are informative about the relative consumption of the various goods. Moreover, when the reallocative shock increases price dispersion, the consumer is pushed away from the unconstrained optimal mix of goods, lowering the agent's utility. We show that with concave utility functions, the agent is risk averse towards these reallocative shocks. Hence, bad relallocative shocks carry a risk premium. Since prices tend to be more dispersed when the agent is pushed further away from the unconstrained optimal mix of the goods, shocks to price dispersion carry a negative risk premium.

We then consider an illustrative setting with two goods and a constant elasticity of substitution (CES) consumption aggregator. We show that high-price goods are risky as they load more negatively onto the reallocative shock when the elasticity of substitution between the goods is greater than one (as we show is the case in the data). To understand the economic rationale for this, consider a reallocative shock that moves output away from the unconstrained optimal mix of the two goods by lowering (increasing) the output of good one (two). This shock will increase the price of the now scarcer good one. However, if the elasticity of substitution is greater than one, then this shock remains detrimental to good one's cash flows as the price increase does not fully offset the output decrease. This causes a drop in the value of the claim to the output of good one (i.e., stock one). Hence, an increase in price dispersion that moves output away from good one lowers the price of stock one, meaning that stock one has a negative loading on the price dispersion shock. As the market price of risk of these dispersion shocks is negative, stock one earns a risk premium.

On the empirical front, we test the prediction that states of high aggregate price dispersion are bad in two ways. First, we estimate the market price of risk of these reallocative shocks via GMM and show that they are not only negatively priced, but they also explain the relative price premium in the data, as our model predicts. Second, we estimate a series of impulse response functions (IRFs) that show when the distribution of output prices becomes more dispersed, macroeconomic quantities, such as output, investment, and consumption tend to fall. In either case, we empirically measure these reallocative shocks using innovations to the degree of cross sectional price dispersion across various categories of goods and services tracked by the U.S. Bureau of Labor Statistics (BLS).

We implement our study by exploiting the granular data compiled by the BLS on the average prices of various types of goods and services. This data disaggregates the headline Consumer Price Index into various sub-components that track the prices of multiple categories of goods and services (e.g., food and medical care). While data on hundreds of highly granular sub-components of CPI are available via the BLS, we are primarily interested in how changes in the cross-sectional distribution of output prices impact asset prices and marginal utility. Thus, we limit our attention to 44 sub-components of headline CPI that can be linked to the CRSP/Compustat universe of firms. Given the close connection between changes in relative prices and quantities consumed, this data allows us to measure how changes in the *relative prices* of goods and services are related to asset prices. These price changes can arise from exogenous shifts in supply or demand (e.g., shocks to consumer preferences or tastes). For clarity and parsimony, our theoretical analysis assumes that price changes are driven by supply-related factors, but we verify that all results remain unchanged if we assume goods prices change in response to exogenously fluctuating demand.

While we implement our study using CPI data constructed and provided by the BLS, we are careful to verify that the relative price premium is not simply a manifestation of inflation-related spreads that have already been documented by the literature. First, our empirical measure of relative prices is defined as the inflation rate of a specific group of goods and services (e.g., food or information technology) minus the headline inflation rate, and so is largely independent of headline CPI by construction. Next, we show that portfolios formed on relative price changes have similar exposures to shocks to the level of inflation measured via, for example, the inflation betas of Boons et al. (2020). Moreover, we show that projecting the relative price premium on the returns of inflation-sorted portfolios from Boons et al. (2020) or Fang et al. (2022) produces positive abnormal returns and highly significant pricing errors. In short, this shows that the relative price premium is distinct from other inflation-related spreads.

Finally, a battery of additional robustness checks also confirm that the relative price premium is unrelated to several common asset-pricing factors and characteristics. For instance, we show that the premium does not simply arise due to differences in investment rates, profitability, markups, and price rigidity between firms with high versus low relative prices. Similarly, the spread is robust to perturbing various aspects of our baseline portfolio formation procedure, such as changing portfolio breakpoints, excluding difficult-to-trade stocks from the analysis, or excluding the more volatile components of inflation from our analysis (i.e., food and energy). Lastly, we also show that the premium is independent of a variety of industry-level effects that could relate to the cross-sectional heterogeneity in relative price that we exploit (e.g., ex ante differences in industry returns, industry momentum, markups, or market power). All in all, these and other robustness checks confirm that the relative price premium is a distinct feature of the data.

Literature review. This paper builds on several bodies of work. Our disaggregation of the total consumption basket into its various components is most similar to Dittmar et al. (2020) who estimate the degree of substitutability between nondurable consumption goods and find that energy consumption represents a distinct type of consumption that influences marginal utility. Similarly, Yogo (2006) studies whether the consumption of durable and non-durable goods can be substituted and find that durable consumption plays an important role in determining asset prices. Likewise, Ait-Sahalia et al. (2004) show that the consumption of luxury versus basic goods is useful for reconciling consumption-based asset-pricing models with the data. In contrast our study explicitly assumes, and also empirically verifies, that the average consumption good are not perfect substitutes of one another, and thus shows that relative price dispersion is a distinct determinant of marginal utility. Other studies featuring heterogeneous goods included, for example, Cochrane et al. (2008); Lochstoer (2009); Martin (2013).

Second, a number of studies examine the extent to which assets can hedge the level of inflation (see, e.g. Fama and Schwert (1977); Fama (1981); Chen et al. (1986); Boudoukh et al. (1994); Campbell and Vuolteenaho (2004); Bekaert and Engstrom (2010); Ang et al. (2012)). Recently, Fang et al. (2022) examines the ability for various assets to hedge core and energy inflation, while Boons et al. (2020) show that stock returns are related to the level of inflation. In contrast to these studies, we decompose the headline inflation rate into over 30 of its sub-components and show that relative price dispersion carries a separate price of risk from shocks to the level of inflation.

Some studies suggest that the inflation risk premia arise from the behaviors and actions of firms. For instance, Eraker et al. (2016) show that inflation's effect on equity valuations depends on the durability of a firm's output. Gorodnichenko and Weber (2016) find that firms with sticky prices have high stock returns volatility, while Bianchi et al. (2022) find that when low inflation times shift to high inflation times, firms experience high equity market return premia since firms gradually adjust valuation ratios. Finally, Bhamra et al. (2022) show how inflation influences equity values through interactions with (sticky) leverage decisions and cash flows.

1 Data

Our study uses data from several sources. CPI data are compiled by the BLS and retrieved from the Federal Reserve Economic Data (FRED) services operated by the Federal Reserve Bank of St. Louis. Monthly stock return data are from the Center for Research in Security Prices (CRSP), while firm-level accounting variables are obtained from Compustat. Return-based asset-pricing factors related to the Fama and French (1993, 2015) three- and five-factor models, and the Carhart (1997) momentum factor, are retrieved from Kenneth French's data library. We obtain the Hou et al. (2021) q^5 factor data from the Global-q library.

1.1 Relative Prices and their dynamics

While many market participants and academics focus on headline, core, and energy CPI (Fang et al., 2022; Boons et al., 2020; Fama and Schwert, 1977; Chen et al., 1986; Boudoukh et al., 1994), these broad indexes can be further disaggregated into numerous subcomponents that provide more granular measures of the price changes associated with various categories of consumption goods and services. For instance, the headline inflation rate can be decomposed into the price changes associated with eight subcategories of goods and services: food and beverages, housing, apparel, transportation, medical care, recreation, education and communication, and other goods and services. These categories of CPI can in turn be further decomposed into their own sub components. For example, the "medical care" index can be decomposed into the costs associated with "medical care commodities," such as prescription drugs, and "medical care services," such as visits to physicians, nursing homes, and health insurance.

To visualize the degree of price dispersion underlying the common headline inflation rate, Figure 1 plots both the annual headline inflation rate (solid blue line) and the annual inflation rates of the various goods and services underlying the headline CPI figure (shaded blue region). While the headline inflation rate is unsurprisingly stable in the period following the Great Moderation in the mid-1980s, the difference between the inflationary and deflationary subcomponents of CPI exceeds 20% per annum at many points in time. This difference also exceeds 30% per annum in many periods. Thus, while the headline inflation rate has remained relatively stable in the recent decades, the degree to which the prices of various goods and services inflate and deflate in price *relative* to the headline inflation figure has historically been, and continues to be, quite pronounced.

We formally measure how the various categories of goods and services underlying the headline CPI are changing over time by defining the relative price change of the k^{th} subcomponent of headline

CPI in the τ-month period preceding time t as

$$RP_{k,t,\tau} = \log\left(\frac{\text{CPI}_{k,t}}{\text{CPI}_{k,t-\tau}}\right) - \log\left(\frac{\text{CPI}_{t}}{\text{CPI}_{t-\tau}}\right). \tag{1}$$

Here, CPI_t ($CPI_{k,t}$) represents the level of (sub component k of) headline CPI at time t. As such, a positive (negative) value of $RP_{k,t,\tau}$ represents a goods or services that has increased (decreased) in price more than headline CPI over the τ months preceding time t. Since the price changes associated with the various types of goods and services are measured *relative* to the headline inflation rate, the appropriately weighted average value of $RP_{k,t,\tau}$ in the economy is zero by definition.[1]

Figure 2 reports the time series variation in relative prices both across all goods and services included in our study (Panel A) and for two specific goods and services underling the core CPI rate (Panel B). To begin, Panel A displays the cross-sectional dispersion, measured using the inter-quartile range, of relative prices changes obtained by setting τ in equation (1) equal to 12. The figure shows that the average dispersion in relative prices hovers around 3.5% per annum. This indicates that there is generally only a 3.5% per annum difference in the price changes associated with half of the goods and services underlying headline CPI. However, this dispersion in prices exceeds 5% in many periods of time, including the onsets of the Global Finance Crisis and the COVID-19 pandemic. The figures also shows that relative price dispersion is both moderately countercyclical, tending to rise during NBER recession, and only moderately correlated with the headline inflation rate. Thus, the distribution of relative price changes tends to vary for reasons largely unrelated to the headline inflation rate.

Given the large amount of time-series variation in relative price dispersion documented in Panel A, Panel B of Figure 2 focuses on the relative price changes associated with two specific goods and services of importance to consumers: the price of new and used automobiles and medical care. The figure demonstrates that while the price of medical care (automobiles) has typically increased by more than (less than) the headline inflation rate over time, the relative prices of these goods and services has exhibited marked shifts over time. Most dramatically, the price of automobiles

[1] Table A.5 in the Online Appendix reports the correlation between relative price dispersion and a host of other financial and macroeconomic indicators. While price dispersion is positively correlated with the level of inflation and macroeconomic uncertainty, and negatively correlated with the level of economic activity, we make sure to control for these and other variables in our upcoming analyses. For instance, Table 4 shows that the relative price premium is unrelated to changes in the level of inflation, while Table 5 demonstrates that relative price dispersion has a negative association with marginal utility that is economically large and incremental to these variables.

increased by roughly 10% more than the headline inflation rate after the onset of the COVID-19 pandemic in March 2020, while the relative price of medical care fell by about 5% in the same period. Similar, albeit more muted, shifts in the relative price of medical care and automobiles were also seen after the Global Finance Crisis in 2010 and 2011.

While the price of automobiles increased significantly more than the price of medical care in 2021, is not clear how these relative price changes impact either the firms that produce the underlying goods and services or the marginal utility of investors who consume these goods and services. On the one hand, and holding all else constant, 2021 was an unambiguously good time for those intent on consuming medical care and an unambiguously bad time for those interested in purchasing new or used automobiles. To the extent that the average investor is more concerned about consuming medical care (automobiles), then 2021 may be considered a good (bad) time for the average investor. On the other hand, in a world where the average economy wide relative price change is zero by construction, it is not obvious that the *dispersion* in relative price constitutes a distinct determinant of an investor's wellbeing. After all, a relative price increase in one market is necessarily accompanied by relative price decreases in other markets, leaving the average impact on the price level equal to the headline inflation rate.

This ex ante ambiguous effect of relative price dispersion on the economy is what prompts us to ask (i) how relative price dispersion impacts the expected returns of firms that provide the goods and services underlying the BLS's CPI data, and (ii) whether there is any relation between relative price dispersion and the average investor's marginal utility (i.e., wellbeing).

1.2 Linking firms to CPI indices

Our empirical analysis requires us to match firms in the CRSP/Compustat universe to the various sub-components of the headline CPI. As this type of link is not available, we create our own in the spirit of Gomes et al. (2009). That is, we match groups of firms identified using their four-digit SIC codes to the various components of CPI.

Since the BLS constructs measures of CPI to reflect average changes in the prices that *consumers* pay for various goods and services, we exclude industries and SIC codes that are associated with the production side of the economy (e.g., mining and wholesale trade). Our baseline analysis also excludes components of CPI that are (i) very granular in nature (e.g., the price of pet food and the cost of fees for lessons), since very few public firms can be matched to these goods and services providers, and (ii) very coarse in nature (e.g., indexes that track the average prices of medical care and food and beverages), as these coarse indexes can be disaggregated into relatively more granular subcomponents of CPI with a sufficient number of public firms to be included in our analysis. For example, we do not include the "medical care" index in our baseline analysis because we include its more granular subcomponents: "medical care commodities" and "medical care services." Our link between the CPI indexes and CRSP/Compustat firms is available upon request.

Our matched sample captures about 40% of the number of public firms in the U.S. economy and about 60% of the total market capitalization of U.S. public equity despite the fact that we exclude financial and production-related firms (for which there are no direct subcomponents of CPI). Moreover, since the BLS has substantially improved its coverage of the set goods and services it tracks and reports data on over time, we start our sample in 2000 as this is around the first year we have a comprehensive cross section of the inflation rates associated with the subcomponents of CPI. Our sample ends in 2022, as this is the most recent year with complete data.

2 Empirical Results

This section establishes the relative price premium — our key empirical fact — and shows that this premium is a distinct and robust feature of the data. We discuss the portfolio formation procedure that we employ in Section 2.1, and then report the portfolio returns (Section 2.2), asset-pricing alphas (Section 2.3), and portfolio characteristics (Section 2.4). Section 2.5 then demonstrates that the relative price premium is (i) independent of spreads based on the level of the inflation rate and the durability of output (Section 2.5.1) and (ii) robust to numerous changes to the portfolio formation procedure described below (Section 2.5.2).

2.1 Portfolio formation based on relative price changes

At the end of each month t from December 1999 to November 2022, we sort industries into portfolios based on the relative price changes associated with the various sub components of CPI from equation (1). In measuring these relative price changes via $RP_{k,t,\tau}$, we set τ equal to three to focus on quarterly changes in relative prices, as these lower-frequency price changes are less transitory in nature and are more likely to be relevant to consumers and investors. We leave a one-month gap between the release of the CPI data and the portfolio formation date to account for potential delay in the reporting of CPI. This helps to ensure that the relative price changes we measure are available to investors in each portfolio formation month.

Specifically, we sort industries into three portfolios on each portfolio formation date such that the high (low) RP portfolio includes all industries with relative price changes at or above (below) the 90^{th} (10^{th}) percentile of the cross-sectional distribution of relative price changes at that point in time. The medium portfolio then includes all industries with relative price changes between these two breakpoints. We hold each portfolio for the three months following each portfolio formation month, resulting in a time series of monthly overlapping returns for each portfolio that ranges from January 2000 to December 2022 (see, e.g., Ang et al. (2006a)). In forming these portfolios, we only include the sub components of CPI that are matched to at least 30 individual firms to ensure that portfolio returns are not driven by idiosyncratic shocks to a small number of firms.

To highlight the importance of the *conditional* portfolio re-balancing procedure described above, Table A.6 in the Online Appendix reports the monthly transitions between the portfolios. The table shows that while relative price changes are somewhat persistent, they are by no means fixed over time. For instance, while about 60% of industries with high (low) relative price changes in month t tend to maintain high (low) relative price changes in month $t + 1$, around 40% of industries transition to the medium portfolio. The fact that these relative price changes are not fixed over time emphasizes the importance of our conditional re-balancing procedure. This also provides us with an early indication that the relative price premium is not simply driven by persistent differences in the degree to which firms in the high and low portfolios can adjust their output prices.

To complement this transition matrix, Figure A.3 in the Online Appendix shows the proportion of months that each industry is assigned to each portfolio. The figure once again confirms that there are many transitions between portfolios as relative prices change over time. Moreover, Figure A.4 in the Online Appendix verifies that the composition of the portfolios does not change markedly with the state of the business cycle. We demonstrate the robustness of our upcoming results to many other aspects of the portfolio formation procedure described above in Section 2.5.

2.2 Portfolio returns

Table 1 reports our central empirical result: the monthly value-weighted returns of the RP-sorted portfolios from January 2000 to December 2022. The table indicates that there is a monotonically increasing relation between relative price changes and average returns, such that firms with the highest relative price change earn an average return of 1.14% per month, while firms with the lowest relative price change earn an average return of 0.26% per month. Thus, a portfolio that buys high RP firms and sells low RP firms, which we denote the *relative price premium*, earns an average return of 0.88% per month. This return spread is not only statistically significant at the 1% level (t-statistic of 3.27) but is also economically large in magnitude. The annualized Sharpe ratio of the relative price premium is roughly 0.6, which is comparable to the Sharpe ratio of the market portfolio over the sample period.

Although we conduct and discuss an extensive set of robustness checks related to the relative price premium in Section 2.5, the remaining columns of Table 1 already provide some early indications that the premium is an economically important aspect of the data. To begin, the table shows that while we implement the portfolio sorts underlying the relative price premium at the *index* level, the resulting portfolios are well balanced in terms of the number of underlying firms. Specifically, both the low and the high RP-sorted portfolios each contain about 150 firms.

First, rather than reporting value-weighted returns, the table shows that the relative price premium is 0.76% per month (t-statistic of 2.70) when equal-weighted returns are used instead. Next, to mitigate the concern that the premium simply captures ex ante heterogeneity in the types of industries that experience high versus low relative price changes (e.g., the possibility that energy firms have both large relative price changes *and* high returns due to their inherent industry risk), the table constructs the premium using industry-adjusted returns. These results are obtained by subtracting the relevant Fama-French 12 industry return from each firm's individual return, and then reconstructing the returns of the RP-sorted portfolios. The results indicate that the premium remains an economically large 0.54% per month and statistically significant at the 5% level (t-statistic of 2.38) even after making this industry adjustment. Thus, the relative price premium does not simply reflect prominent industry-level differences in returns.

Finally, we also ensure that the relative price premium does not simply reflect differences in prominent firm characteristics (e.g., the possibility that firms that experience large relative price changes are typically small firms with high book-to-market ratios and high stock return momentum). We implement this analysis by first subtracting the relevant Daniel et al. (1997) benchmark return from each firm's stock return and recomputing the returns of the RP-sorted portfolios. The results indicate that the characteristic-adjusted premium is also about 0.54% per month and significant at the 5% level (t-statistic of 2.44). This reassures us that the premium does not merely represent a transformation of the prominent size, value, and momentum effects.

2.3 Portfolio alphas

Table 1 shows that firms in industries that have experienced the highest relative price increases outperform firms in industries that have experienced the lowest relative price increases by 0.88% per month, resulting in the relative price premium. To examine whether this premium is explained by common unconditional asset-pricing models, we project the premium's monthly value-weighted returns on the factors underlying six asset-pricing models: the CAPM, the Fama and French (1993) three-factor model, Carhart (1997) four-factor model, Fama and French (2015) five- and six-factor model, and the q^5 model of Hou et al. (2021).

The results, reported in Table 2, show the monthly alphas and factor loadings of the relative price premium. These alphas are economically large and range from 0.71% per month for the q^5 model (t-statistic of 2.13) to 1.03% per month for the CAPM (t-statistic of 4.02). The factor loadings associated with these projections also show that the relative price premium's returns are highly countercyclical, as the market betas of the spread range from -0.21 (t-statistic of -2.30) to -0.31 (t-statistic of -3.39). Since the returns of the relative price premium tend to be high when excess market returns are low, exposure to market risk is unable to explain the premium. Moreover, the premium shows little relation to prominent asset-pricing factors related to size, value, momentum, profitability, and (expected) investment rates. This leads us to propose a cohesive risk-based explanation for the relative price premium in Section 3.

2.4 Portfolio characteristics

Accounting and return-based characteristic. Panel A of Table 3 sheds light on the types of industries underlying each of the RP-sorted portfolios by reporting the average accounting and return characteristics of each portfolio. The results show no differences in these portfolios in terms of book-to-market ratios, quarterly asset growth (Cooper et al., 2008), and idiosyncratic stock return volatility (Ang et al., 2006b). While the high RP-sorted portfolio features larger and less profitable firms with high returns in the prior month, neither the size spread, the gross profitability premium of Novy-Marx (2013), nor the short-term reversal effect of Jegadeesh (1990) can explain the relative price premium. This is because large firms, less profitable firms, and firms with high prior month returns are expected to earn low, rather than high, average returns. Likewise, there are no differences in standardized unexpected earnings across the RP-sorted portfolios. This means that the premium does not simply reflect the possibility that high RP industries tend to generate better than expected earnings, leading to earnings surprises and a positive stock market reaction.

The only characteristic in Panel A that is significantly different between the low and high RP-sorted portfolios and related to a return spread that is aligned with the relative price premium is the momentum effect of Jegadeesh and Titman (1993). Notably, the table shows that the high RP portfolio is comprised of stocks with marginally higher stock return momentum than stocks in the low RP portfolio (t-statistic of 1.87). While this difference in momentum is relatively small, we nevertheless establish that the momentum effect does not drive our results in three ways.

First, and most directly, Table A.16 in the Online Appendix conducts a conditional portfolio sort and constructs the relative price premium within momentum-sorted portfolios. The results show that the premium remains economically large (at least 0.60% per month) and statistically significant at the 5% level within both low and high momentum portfolios. Second, to the extent that the momentum characteristic is related to the momentum factor of Carhart (1997), we emphasize that the relative price premium produces large and statistically significant alphas with respect to models that include this factor (recall columns (3) and (5) of Table 2). Finally, Table A.11 in the Online Appendix augments the results underlying Table 2 with the industry momentum spread of Moskowitz and Grinblatt (1999), another variety of return momentum. The relative price premium's alpha remains positive and statistically significant event after accounting for this extra type of momentum. Thus, small differences in momentum do not drive the relative price premium.

Concentration, markups, price rigidity. Beyond the battery of characteristics discussed above, Panel A of Table 3 also reports the Herfindahl-Hirschman Index (HHI) of each underlying portfolio, the average markups of the underlying firms, estimated using the approach of De Loecker et al. (2020), and the measure of price rigidity from Pasten et al. (2020). The results indicate that the high RP-sorted portfolio tends to feature firms in slightly less concentrated industries that, naturally, charge slightly lower markups. This suggests that the relative price premium cannot be explained by the fact that firms with higher market power tend to not only charge high prices but also have higher expected returns (e.g., Corhay et al. (2020)). Likewise, these same firms do not appear to have less flexible output prices than low RP firms, suggesting that the relative price premium does not simply reflect the risks associated with nominal rigidities (Weber, 2015).

Inflation betas. To examine the degree to which the relative price premium covaries with various aspects of inflation, Panel B of Table 3 reports the exposure of the relative price premium to the inflation shocks constructed by Boons et al. (2020) and, motivated by Fang et al. (2022), inflation shocks related to the headline, core, energy and food CPI indexes (see Section A.1 of the Online Appendix for details on the construction of each inflation beta). The results indicate that the relative price premium is unrelated to the measure of inflation shocks discussed by Boons et al. (2020), shocks to energy-related inflation, and shocks to food-related inflation. However, the high and low RP portfolios have significantly different exposures to shocks to both headline and core inflation. Notably, the high RP portfolio tends to earn relatively lower returns than the low RP portfolio when positive shocks to headline and core inflation are realized. The next section formally verifies that inflation-related spreads do not drive the relative price premium despite this difference between the portfolios' exposures to inflation shocks.

2.5 Independence from related spreads and robustness

This section demonstrates that the relative price premium is (i) distinct from return spreads related to the *level* of inflation, (ii) not driven by the durability premium of Gomes et al. (2009), and (iii) robust to varying the portfolio formation procedure described in Section 2.1.

2.5.1 Independence from inflation- and durability-related spreads

Our key variable of interest is the degree to which relative prices differ across various consumption goods and services, as measured by equation (1). While this equation clearly shows that relative price dispersion is independent of the headline inflation rate, our results are yet to confirm that the relative price premium is materially distinct from return spreads related to the level of inflation (e.g., the inflation spread of Boons et al. (2020). After all, if periods of high (low) relative price dispersion simply coincide with times in which the level of the headline inflation rate is high (low), then the relative price premium may represent a transformation of the known inflation premium in asset returns. A close examination of Figure 2 shows that this is a potential concern, as increases in the headline inflation rate often coincide with increases in relative price dispersion. In fact, the headline inflation rate reported in this figure is moderately positive correlated with the inter-quartile range of relative prices ($\rho = 0.44$).

Table 4 confirms that the relative price premium is independent of four spreads related to the level of inflation: the spread documented by Boons et al. (2020) and, motivated by Fang et al. (2022), the return spreads based on differences in each firm's exposure to headline, core, and energy inflation, respectively. We establish the independence of the relative price premium from these spreads by projecting the returns of the premium on the returns of each of these inflation-related spreads. We then report the alpha that emerges from each of these regressions. Here, an economically large and statistically significant alpha indicates that the relative price premium is not simply a linear transformation of an inflation-related spread. The results in Columns (1) to (4) of Table 4 show that the alphas associated with the relative price premium exceed 0.87% per month and are significant at the 1% level regardless of which inflation-based spread we control for. This highlights that the relative price premium is not simply a reflection of a known relation between shocks to the level of inflation and asset prices.[2]

Accounting for output durability. Column (5) ensures that our results are not simply a manifestation of the durability effect of Gomes et al. (2009). We establish this fact by following an empirical procedure that is similar to that underlying Columns (1) to (4). That is, we project the relative price premium on the durability spread and record the resulting alpha. The results indicate that the relative price premium has an alpha of 0.87% per month with respect to the durability spread (t-statistic of 3.26). This alpha increases to 1.03% per month (t-statistic of 4.13) when we also control for excess market returns in Table A.17 of the Online Appendix. Thus, the relative price premium does not simply reflect the output durability effect of Gomes et al. (2009).

[2]Moreover, Table A.17 in the Online Appendix shows that a similar result holds if we also control for the excess returns of the market portfolio. Here, the alphas of the relative price premium rise to at least 1.03% per month and remain significant at the 1% level.

2.5.2 Robustness to variations in the portfolio formation procedure

This section shows that the relative price premium is robust to different implementations of the portfolio formation procedure described in Section 2.1. While most results are reported in Section A.6 of the Online Appendix for brevity, we discuss the key takeaways below.

Portfolio breakpoints. Our benchmark analysis sorts industries into portfolios using the 10^{th} and 90^{th} percentiles of the cross-sectional distribution of relative price changes from equation (1) as portfolio breakpoints. In Panel A (Panel B) of Table A.7 we use the 20^{th} and 80^{th} (30^{th} and 70^{th}) percentiles of this cross-sectional distribution instead. This essentially doubles (triples) the number of industries included in the extreme portfolios, ensuring that our baseline results are not driven by a small number of industries with persistently low or high relative prices changes. The results demonstrate that the relative price premium remains economically large and statistically significant in either case. For instance, the premium is 0.49% per month and significant at the 1% level (t-statistic of 2.75) in Panel B when we use the most conservative breakpoints.

Excluding food or energy. Table 1 shows that cross-sectional differences in the relative price changes of the sub components of headline CPI are related to future stock returns. Although these results are based on a comprehensive set of price indices, this large set of price indexes includes food and energy prices, which are typically more volatile than other components of CPI. To ensure that the relative price premium is not simply an artifact of including food or energy firms in our sample, Table A.8 reports the results obtained by repeating our analysis without these firms. The results show that (i) the portfolio returns remain monotonically increasing and (ii) the relative price premium remains economically large and statistically significant after excluding these firms.

Limits-to-arbitrage. Table A.15 makes sure that the relative price premium is not driven by limits-to-arbitrage by removing difficult-to-trade firms from the analysis. In particular, the table reports the premium constructed within the set of stocks with share prices exceeding \$5 per share on the portfolio formation date (Panel A), above median market capitalization (Panel B), and below median values of idiosyncratic volatility (Panel C). In each case, the relative price premium remains economically large (at least 0.60% per month) and statistically significant (t-statistics for the spread exceed 2.45 in each Panel). Thus, limits- to-arbitrage cannot explain the relative price premium, reinforcing the need for the relation explanation for the premium in Section 3.1.

Overlapping returns. Given the relatively short time period for which a broad cross section of relative price data are available, we use overlapping returns to make statistically efficient use of the time-series dimension of the data (see, e.g., Ang et al. (2006a)). This, however, induces a moving-average effect in the standard errors associated with portfolio returns. While we already address the overlapping nature of the data via our use of Newey and West (1987) standard errors with an appropriate number of lags, Ang and Bekaert (2007) suggest that the use of Hodrick (1992) standard errors may be more appropriate in these instances.

In light of this point, we ensure that our use of overlapping data does not drive the relative price premium in two ways. First, Panel A of Table A.9 simply repeats the analysis underlying Table 1 but reports Hodrick (1992) standard errors in place of Newey and West (1987) standard errors. The results show that the relative price premium remains significant at the 1% level (t-statistic of 3.27). Second, Panel B repeats the analysis with non-overlapping portfolio returns and shows the premium remains economically sizable at 0.70% per month and statistically significant at the 5% level. Thus, the use of overlapping returns does not drive our key results.

Including more granular and coarse price indexes. Our benchmark analysis requires us to create a link between the CRSP/Compustat universe of firms and the various price indexes constructed and published by the BLS. In doing so, we exclude (i) price index that are very granular in nature (i.e., those for which fewer than 30 firms can be matched) and (ii) price indexes that are very coarse and can be decomposed into sub-indexes for which we can match a sufficient number of firms (e.g., we exclude the "medical care" index because we have a sufficient number of firms to include its two sub-indexes: "medical care commodities" and "medical care services").

Table A.10 considers the extent to which these choices drive our result and shows that neither choice has a material impact on our results. For instance, Panel A shows that the relative price premium is 0.72% per month and significant at the 1% level when we include all indexes that can be matched to at least five, rather than 30, public firms. Likewise, Panel B shows that the relative price premium remains significant when coarse indexes, such as medical care, are included alongside their more granular sub components. The relative price premium is 0.86% per month in this case and also statistically significant at the 1% level.

Accounting for real-time vintages of data. Our baseline analysis employs CPI data from FRED to construct the relative price premium. Although we mitigate the effect of data revisions by ensuring that there is a one-month interval between the release of each month's CPI data and when we use this data to form the RP-sorted portfolios, this one-month interval does not necessarily eliminate the possibility that the CPI data is further revised (Ghysels et al., 2018). Thus, to ensure that our results are not driven by these types of data revisions, we re-construct the relative price premium using real-time vintages of CPI data from ALFRED. The results, reported in Table A.12 of the Online Appendix, show that our results are robust to this dimension of our analysis. Namely, the relative price premium constructed with this ALFRED data is 0.77% per month and statistically significant at the 1% level.

Excluding conglomerates. To ensure that our results are not driven by the fact that some firms operate across a variety of business line and sell various types of products and services, we reconstruct the relative price premium after removing all conglomerate firms from our samples. This helps to ensure that each firm is matched to the most appropriate price index to which the firm belongs. We identify conglomerate firms following the definition of Hoberg and Phillips (2018) and report the results of this analysis in Table A.13 of the Online Appendix. The results show that the resulting relative price premium is both economically large (0.97% per month) and statistically significant (t-statistic of 2.96) when we exclude conglomerate firms.

Importance of conditional sorting. To demonstrate the importance of the *conditional* portfolio formation procedure described in Section 2.1, we consider an alternative *unconditional* portfolio formation procedure. Specifically, we permanently assign each index to a single portfolio based on the index's average relative price change over the sample period. The results of this unconditional analysis show that the resulting return spread is -0.05% per month and statistically insignificant (t-statistic of -0.17). This not only highlights that there is a large degree of conditional variation in relative price changes but also confirms that the premium is not driven by fixed differences in relative price changes across industries (e.g., medical care becoming increasingly expensive while IT hardware becomes increasingly cheap).

Measuring relative prices over alternative horizons. In defining relative price changes via equation (1, our baseline analyses sets τ equal to three and computes these price changes over the previous quarter. Table A.19 of the Online Appendix consider the case in which we compute these price changes over horizons of either six months (i.e., $\tau = 6$) or 12 months (i.e., $\tau = 12$). The results indicate that a relative price premium that exceeds 0.60% per month arises in either case.

Thus, the baseline results are robust to this perturbation in the portfolio formation process.

Focusing on larger sub-components of CPI. Our analysis suggests that firms that have undergone a higher relative price change tend to be riskier than those that have undergone a smaller relative price change. Economically, we suggest that this relation arises because investors are particularly averse to states of the world in which certain goods become scarcer than others. As a result, the risk premium of the scarce asset increases. Given the various sub-components of CPI carry a different weight in the average consumer's consumption bundle, it is natural to expect this result to be particularly pronounced among the set of goods and services that carry a larger weight. We test and confirm this hypothesis in Table A.18 of the Online Appendix, which shows that the relative price premium is 1.06% per month (t-statistic of 3.64) among the set of goods and services that have an above-median weight in the average consumer's consumption bundle.

Excluding economic recessions. Given Figures 1 and 2 show that relative price dispersion is somewhat countercyclical, we examine whether the relative price premium is driven by key recessions in our sample period. Table A.21 in the Online Appendix reports the results. Panel A (Panel B) shows that the premium is not driven by the recent COVID-19 pandemic (the Global Finance Crisis), as the premium exceeds 0.74% per month when we exclude either of these periods. More tellingly, Panel C verifies that the premium remains 0.65% per month (t-statistic of 2.44) if we exclude all recessions from our sample period, including the recession of the early 2000s. Thus, the relative price premium is is not driven by relatively high expected returns during recessions.

3 Reconciling the facts

The key novel fact from our empirical analysis is the existence of a relative price premium, whereby firms whose output prices have experienced the largest average increase over the last quarter outperform those that have experienced the lowest price increase over the last quarter by 0.88% per month. In this section we both propose and test a rational explanation for the relative price premium. In particular, Section 3.1 outlines a consumption-based asset-pricing framework that predicts that high price dispersion states are associated with high marginal utility (i.e., bad times for investors). Section 3.2 then tests the key implications of this model via generalized method of moments (GMM) and shows that high relative price dispersion states are not only associated with a negative market price of risk, but the relative price premium has a negative covariance with this priced source of risk.

3.1 Consumption-based asset-pricing framework

To fix ideas, we want to focus on two key dimensions of consumption risk – the level and the distribution across goods. We start by considering a general setting with N goods and show that dispersion is priced. Next, we focus on a specific workhorse utility specification, namely constant relative risk aversion (CRRA) preferences with a constant elasticity of substitution (CES) aggregator over two goods. We show explicitly how the redistribution across goods is priced and that under certain conditions on the elasticity of substitution, high price goods require a premium.[3]

3.1.1 General setting with N goods and concave utility

Consider an endowment economy with N goods. For ease of exposition, we start by considering a static economy in which a representative agent has a strictly concave utility function $u(\boldsymbol{c})$, where $\boldsymbol{c} = (c_1, \ldots, c_n)$ is the N-dimensional vector of the agent's consumption of each good. To separate the level of consumption from the distribution of consumption across goods, assume that $\sum_n^N c_n = C > 0$. That is, we consider how the agent allocates consumption across the N goods, subject to the requirement that the sum of the quantities of the two goods is equal to the strictly positive quantity C. Let $p_{i,j}$ denote the price of good j relative to that of good to i. In equilibrium, these relative prices are $p_{i,j} = \frac{u_j(\boldsymbol{c})}{u_i(\boldsymbol{c})}$, where $u_k(\boldsymbol{c})$ denotes the partial derivative of the utility function with respect to good $k = 1, \ldots, N$. We have the following result.

Proposition 1. *When the representative agent can freely choose how to allocate consumption across the N goods, subject to the constraint $\sum_n^N c_n = C > 0$, then $p_{i,j} = 1$ for all $i, j = 1, \ldots, N$*

Proposition 1 shows that when the representative agent can freely choose the mix of the goods, then the relative prices are all equal to one. Hence, there is no price dispersion in this case. Next, let $\boldsymbol{c}^*$ denote the optimal mix of goods and consider another allocation $\hat{\boldsymbol{c}} = \boldsymbol{c}^* + y\boldsymbol{e}$, where $y \in [0, 1]$ and $\boldsymbol{e} = (e_1, \ldots, e_N)$ is an N-dimensional vector that satisfies $\sum_{n=1}^N e_n = 0$ and $-e_n < c_n$ for all

[3] The workhorse model with CRRA preferences and a CES aggregator suffers from the standard puzzles in the asset-pricing literature, such as the equity premium puzzle, the risk-free rate puzzle, and the excess volatility puzzle. Hence, our focus here is on the qualitative results.

n, with at least one $e_n > 0$. In the above, an increase in y moves $\hat{\boldsymbol{c}}$ further away from the optimal mix of the goods $\boldsymbol{c}^*$. Hence, relative prices will also move away from being jointly equal to one.

Proposition 2. *Define the function* $u(y) = u(\boldsymbol{c}^* + y\boldsymbol{e})$*, where* $y \in [0,1]$ *and* $\boldsymbol{e} = (e_1, \ldots, e_N)$ *satisfies* $\sum_{n=1}^{N} e_n = 0$ *and* $e_n < c_n$ *for all* n *with at least one* $e_n > 0$*, then we have that* $u(y)$ *is decreasing and concave.*

Since $u(y)$ is a concave function, the representative agent requires a risk premium to bear variations in y. Moreover, as utility is decreasing in y, there will be a negative risk premium associated with positive shocks to y. Since higher values of y are associated with higher price dispersion, we have that price dispersion carries a negative market price of risk.

3.1.2 Specific setting with two goods and constant relative risk aversion

To further illustrate how reallocative shocks are priced and show how these reallocative shocks are related to price dispersion, we consider a two-good economy with the following preferences

$$U_{C_t} = E_t\left[\int_t^{\infty} e^{-\rho u}\frac{\hat{C}_u^{1-\gamma}}{1-\gamma}du\right]. \tag{2}$$

Here, time is continuous, $\rho > 0$ is the representative agent's time discount rate, γ represents the agent's coefficient of relative risk aversion, and $\hat{C}_t$ represents the aggregate consumption of the investor at time t. In this two-good economy, we assume that the agent's aggregate consumption is given by the following constant elasticity of substitution (CES) function

$$\hat{C}_t = \left[\alpha^{\frac{1}{\eta}} c_{1,t}^{\frac{\eta-1}{\eta}} + (1-\alpha)^{\frac{1}{\eta}} c_{2,t}^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}, \tag{3}$$

where $c_{1,t}$ and $c_{2,t}$ are the consumption levels for goods one and two at time t, respectively. Moreover, α is the weight placed on the consumption level of good one and η is the elasticity of substitution between goods one and two. We assume that the good one and two are not perfect substitutes, implying that η is finite. Section A.4 in the Online Appendix empirically validates this assumption using data from the Bureau of Economic Analysis (BEA) National Income and Product Accounts (NIPA) and shows that the average value of η is about 1.61 for the typical pair of consumption goods. This suggests that most pairs of goods tend to be substitutes rather than complements.

As we want to focus on fluctuations in both the level and the distribution of consumption, we separate these two dimensions by assuming that $c_{1,t} = s_t C_t$ and $c_{2,t} = (1 - s_t) C_t$, where C_t represents the total level of consumption and s_t is the reallocative process. Trivially, we have that $c_{1,t} + c_{2,t} = C_t$. If the representative agent could freely choose the mix of the goods, then s_t would not only equal α but the relative prices of the two goods would also equal one for all times t. Moreover, since we have two goods, we can map y from Proposition 2 above to s_t, as for any $\boldsymbol{e}$ we must have $e_1 = -e_2$. hence, defining $y_t = |\alpha - s_t|$, we have that price dispersion is increasing in y_t. We assume that aggregate consumption evolves according to

$$\frac{dC_t}{C_t} = \mu_c d_t + \sigma_c dW_t^c. \tag{4}$$

and the share of each good available follows the dynamics

$$ds_t = \kappa(\bar{s} - s_t)dt + s_t (1 - s_t) \sigma_s dW_t^s, \tag{5}$$

where s represents the "long-run" share of aggregate consumption transformed into good one and κ reflects the speed at which the share returns to its long-run mean. In the above, we assume that W_t^c and W_t^s are independent Brownian motions so that we can focus on the separate roles of shocks to the level and the cross-sectional composition of consumption in equilibrium.

Equation (4) essentially imposes a resource constraint on the economy, as total consumption cannot exceed the value of C_t at any time t. This equation also highlights that the first source of uncertainty and risk in this economy is related to the level of consumption, represented by the process W_t^c. The risks associated with shocks to aggregate consumption are addressed by Lucas (1978), Breeden (1979), and much of the ensuing consumption-based asset-pricing literature. However, while many subsequent models in this literature focus on the uncertainty related to the *level* of consumption, most of these models are silent about the potential risks associated with changes in the *composition* in the types of goods that the representative investor is consuming (e.g., the risks associated with consuming too much of good one and too little of good two).

We use the consumption bundle $\hat{C}_t$ from equation (3) as the numeraire. Equipped with this numeraire, the next proposition shows the equilibrium prices of the goods.

Proposition 3. *When the consumption bundle $\hat{C}_t$ is the numeraire, the price of good $i = 1, 2$, $p_{i,t}$ is*

$$p_{i,t} = \left(\alpha_i \frac{\hat{C}_t}{c_{i,t}} \right)^{\frac{1}{\eta}} \tag{6}$$

where $\alpha_1 = \alpha$ and $\alpha_2 = 1 - \alpha$.

Using the consumption bundle $\hat{C}_t$ from equation (3) as the numeraire allows us to express the stochastic discount factor (SDF) in this economy as

$$\begin{aligned} M_t &= \left(\hat{C}_t \right)^{-\gamma} \\ &= \left(\left[\alpha^{\frac{1}{\eta}} \{ s_t C_t \}^{\frac{\eta-1}{\eta}} + (1-\alpha)^{\frac{1}{\eta}} \{ (1-s_t) C_t \}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \right)^{-\gamma} \\ &= (C_t X_t)^{-\gamma}, \quad \text{where } X_t \equiv \left[\alpha^{\frac{1}{\eta}} s_t^{\frac{\eta-1}{\eta}} + (1-\alpha)^{\frac{1}{\eta}} (1-s_t)^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \end{aligned} \tag{7}$$

This equation shows that the SDF in this economy takes on the standard form of an SDF in a continuous time endowment economy in which the representative agent possesses CRRA utility. Moreover, equation (7) also highlights how marginal utility depends on two sources of risk in this economy. First, marginal utility depends on the *level* of aggregate consumption, C_t, which is driven by the shocks dW_t^c. As a positive dW_t^c shock increases C_t, marginal utility decreases in C_t. In contrast, the effect of X_t on marginal utility is more nuanced and depends on the interaction between an investors *preferred* consumption bundle (as determined by the parameters of the CES aggregator) and exogenous shocks to the consumption share s_t. The next proposition characterizes the market prices of risk for the two shocks in the economy.

Proposition 4. *The market price of risk for the shock to the level of consumption, θ_t^c, is*

$$\theta_t^c = \gamma \sigma_c, \tag{8}$$

and the market price of risk for the reallocation shock, θ_t^s, is

$$\theta_t^s = \gamma \left(s_{\beta,t} \sigma_s \left(1 - s_t\right) - \left(1 - s_{\beta,t}\right) \sigma_s s_t \right) \tag{9}$$

where

$$s_{\beta,t} = \frac{\alpha^{\frac{1}{\eta}} s_t^{\frac{\eta-1}{\eta}}}{\alpha^{\frac{1}{\eta}} s_t^{\frac{\eta-1}{\eta}} + (1-\alpha)^{\frac{1}{\eta}} (1-s_t)^{\frac{\eta-1}{\eta}}} \tag{10}$$

Proposition 4 shows that the market price of risk for the shock to the level of consumption is the same as that in a one-good economy with CRRA preferences. Moreover, if $\sigma_s > 0$, then equations (9) and (10) show that the market price of risk associated with the reallocative shock is positive when $s_t < \alpha$, is equal to zero when $s_t = \alpha$, and is negative when $s_t > \alpha$.

To gain better understanding of how the shock to s_t impacts relative prices, price dispersion, prices of risk and the risk premia for the stocks, we plot these quantities in Figure 3. The top left panel shows the price dispersion of the two goods measured as the cross-sectional standard deviation of price of good one and two. As we can see, the further away the s_t is away from $\alpha = 0.5$, the higher the price dispersion. From the top right panel, we see that for $s_t < \alpha = 0.5$ the price of good one is higher, and reverse is true for good two.

As a positive shock to s_t causes prices to become less dispersed when $s_t < \alpha$, then price dispersion loads negatively onto the s_t shock in this range. In contrast, when $s_t > \alpha$, a positive shock to s_t causes prices to become even more dispersed. Hence, price dispersion loads positively onto the s_t shock in that range. As a result, the model indicates that increases in price dispersion carry a negative market price of risk. This can be seen in the bottom left panel where we plot the price of the shock to the level and dispersion. In regard to the level shock, we see that the price of risk is constant, consistent with models with CRRA preferences and i.i.d consumption growth.

As our economy features two firms, each of which is a claim to the cash flows associated with one of the two goods, we can illustrate how shocks to the distribution of consumption (i.e. s_t) affect risk premia. While there are no closed form solutions for stock price dynamics in this model, we can obtain explicit solutions that are straightforward to solve using Monte Carlo simulations. The following proposition outlines the key quantities we need to consider.

Proposition 5. *The price of stock i is*

$$S_{i,t} = E_t \left[\int_t^\infty \frac{M_u}{M_t} p_{i,u} c_{i,u} du \right]. \tag{11}$$

The total instantaneous return is given by

$$dR_{i,t} = \frac{dS_{i,t} + p_{i,t}c_{i,t}dt}{S_{i,t}} = \mu_{R_i,t}dt + \sigma^C_{R_i,t}dW^C_t + \sigma^s_{R_i,t}dW^s_t \tag{12}$$

where $\mu_{R_i,t} = r_t + \sigma^C_{R_i,t}\theta^C_t + \sigma^s_{R_i,t}\theta^s_t$*, and where*

$$\sigma^C_{R_i,t} = \sigma_{p_i,t} + \theta^C_t + \frac{E_t\left[\int_t^\infty M_u p_{i,u}c_{i,u}\left(\mathcal{D}^C_{t,u}log\left(M_u\right) + \mathcal{D}^C_{t,u}log\left(p_{i,u}\right) + \mathcal{D}^C_{t,u}log\left(c_{i,u}\right)\right)du\right]}{E_t\left[\int_t^\infty M_u p_{i,u}c_{i,u}du\right]} \tag{13}$$

and

$$\sigma^s_{R_i,t} = \sigma_{p_i,t} + \theta^s_t + \frac{E_t\left[\int_t^\infty M_u p_{i,u}c_{i,u}\left(\mathcal{D}^s_{t,u}log\left(M_u\right) + \mathcal{D}^s_{t,u}log\left(p_{i,u}\right) + \mathcal{D}^s_{t,u}log\left(c_{i,u}\right)\right)du\right]}{E_t\left[\int_t^\infty M_u p_{i,u}c_{i,u}du\right]}, \tag{14}$$

where $\sigma_{p_i,t}$ *is the diffusion coefficient of the relative price using the CES basket as the numeraire,* $\mathcal{D}^C_{t,u}$ *and* $\mathcal{D}^s_{t,u}$ *represents the Malliavin derivative operators relative to the shock to* c *and* s *at time* t *for period* $u > t$ *for good* $i \in \{1, 2\}$*.*

The bottom right panel of Figure 3 plots the risk premia on stocks one and two respectively. The figure highlights that the risk premium on stock one is higher when $s_t < 0.5$, while the opposite is true when $s_t > 0.5$. Note that when $s_t < 0.5$, the price of good one is higher than that of good two, as good one is relatively scarce. Therefore, the model shows that stocks that are claims to goods with high prices are risky in this economy.

This prediction is, however, sensitive to the value of the elasticity of substitution, as we obtain the opposite result when $\eta < 1$. When $\eta < 1$ and the goods are complements, goods with higher prices will be less risky than those with lower prices. The reason is that a reallocative shock that causes the output of a good to drop will also cause the good's price increase to more than offset the decline in output. Thus, a negative shock to the firm's output will ultimately increase the firm's cash flows if the two goods are complements.

Section A.4 in the Online Appendix empirically distinguish between the case of $\eta > 1$ (shown in Figure 3) and the counterfactual case of $\eta < 1$ (discussed above) by estimating the average elasticity of substitution between pairs of consumption goods underlying the BEA's NIPA tables. We find that the average elasticity of substitution between consumption bundles in the data is $\eta \approx 1.61$.

Moreover, we reject the null hypothesis that $\eta \leq 1$ at the 5% level of statistical significance. Collectively, this evidence indicates that the typical pair of consumption goods in the data are in fact substitutes and the predictions in Figure 3 are empirically relevant.

3.2 Testing the model's implications

This section formally tests whether changes in the cross-sectional distribution of consumption, as proxied by relative price dispersion, carry the negative and statistically significant market prices of risk predicted by our economic framework. We do so by performing the standard linear factor asset-pricing test using GMM. Specifically, equation (7) of our consumption-based asset-pricing framework indicates that marginal utility depends on two sources of aggregate risk: shocks to the level of consumption growth and shocks to the cross-sectional composition of consumption. Thus, we posit the following two-factor SDF:

$$M_t = 1 - b^{MKTRF}\text{MKTRF}_t - b^{\text{Macro}}\text{Macro}_t. \tag{15}$$

Here, MKTRF_t represents the excess returns of the market portfolio at time t, which is our proxy for the *level* of economic activity, and Macro_t represents the innovations to various macroeconomic time series that can potentially explain the relative price premium. Our primary candidate for Macro_t is the log first difference of the cross-sectional distribution of relative price changes, measured using the inter-quartile range of $RP_{k,t}$. However, we also examine whether innovations to the corporate default spread, macroeconomic uncertainty from Ludvigson et al. (2021), aggregate liquidity from Pástor and Stambaugh (2003), intermediary capital from He et al. (2017), and shocks to either core or energy inflation measured in the spirit of Fang et al. (2022) can explain the returns of the relative price premium. Finally, b^{MKTRF} and b^{Macro} capture the market prices of risk of the market factor and the macroeconomic innovations, respectively.

We estimate the market prices of risk (b^{MKTRF} and b^{Macro}) using the standard Euler equation

$$\mathbb{E}\left[\left(1 - b^{MKTRF}\text{MKTRF}_t - b^{\text{Macro}}\text{Macro}_t\right) R^e_{i,t}\right] = 0, \tag{16}$$

where $R^e_{i,t}$ represents the excess return of test asset i in month t. We employ two sets of test assets to estimate these market prices of risk: (i) five quintile portfolios sorted on relative price changes, and (ii) a comprehensive set of test assets that augments the first set of test assets with five industry portfolio, six portfolios sorted on size and book-to-market, six portfolios sorted on size and investment, and size portfolios sorted on size and momentum. Moreover, we also consider the special case of a single-factor SDF that only includes the market factor. This single-factor model, which is equivalent to the CAPM, allows us to assess the relative importance of innovations to the macroeconomic factors for explaining the relative price premium.

Prices of risk. Panel A of Table A.20 reports the market prices of risk associated with excess market returns and innovations to key macroeconomic variables from estimating equation (16) using portfolios sorted on relative prices. The key takeaway from this table is that while the level of aggregate economic activity almost always carries a positive and statistically significant market price of risk, innovations to relative price dispersion carry a negative and statistically significant market price of risk. That is, increases in relative price dispersion signal bad times for investors. This fact also continues to hold in Panel B when we expand the set of test assets to a broader set of portfolios. The market price of risk of relative price dispersion remains negative and is statistically significant at the 1% level (t-statistic of -6.00) among this more comprehensive set of test assets. In fact, while several macroeconomic variables either change sign or lose significance when moving between Panels A and B, the negative market price of risk associated with relative price dispersion remains a robust feature of the data.

Alternative test assets. Beyond the evidence described above, Table A.20 in the Online Appendix demonstrates that innovations to the relative price premium are also priced among a comprehensive set of test assets that do include any of the RP-sorted portfolios. Specifically, the table shows that innovations to relative price dispersion carry a negative price of risk among: (i) 25 portfolios sorted on size and book-to-market ratios, (ii) six portfolios sorted on size and investment, (iii) six portfolios sorted on size and profitability, and (iv) 37 portfolios comprised of the previous three sets of test assets, and (v) the same 37 portfolios plus the returns of the 17 Fama-French industry portfolios. Collectively, this evidence shows that innovations to relative price dispersion do indeed signal high marginal utility states.

Business cycle variation. Overall, the evidence in Panels A and B of Table 5 indicates that innovations to relative price dispersion carry a negative market price of risk. That is, periods of increased price dispersion signal bad times for investors. In line with this evidence from asset prices, Section A.2 of the Online Appendix shows that increases in relative price dispersion also predict deteriorations in key business cycle variables. Notably, we estimate smooth local projections (Barnichon and Brownlees, 2019) that show that a one-standard deviation increase in relative price dispersion predicts declines in the growth rates of industrial production, personal income, and consumption, and an increase in unemployment, even after we condition on the current inflation rate, the term and default spreads, and market returns. This business cycle variation provides external validity to the claim that high price dispersion states are bad for investors and the economy.

Pricing errors. Panels A and B of Table 5 demonstrate that increases in relative price dispersion carry a negative market price of risk and signal bad times for investors. However, the aforementioned results do not establish whether innovations in relative price dispersion help to explain the relative price premium. To address this question, Panel C reports the pricing errors associated with the GMM estimation underlying equation (16).[4]

There are three key takeaways from Panel C. First, a one-factor model (i.e., the CAPM) is unable to explain the returns of the relative price premium. This is shown in the leftmost column of Panel C, in which the pricing error of the relative price premium is 0.84% per month (t-statistic of 3.98). Second, a two-factor model that augments the CAPM with innovations in relative price dispersion renders the pricing error associated with the relative price premium as insignificant. The pricing error implied by this two-factor model is 0.26% per month and statistically indistinguishable from zero (t-statistic of 1.29). Finally, the remaining columns of Panel C indicate that augmenting the CAPM with innovations to any other prominent macroeconomic variable is unable to reconcile the relative price premium.[5] To the extent that changes in the dispersion of relative prices are related to the cross-sectional distribution of consumption, this result is closely aligned with our economic framework in Section 3.1.

Risk exposures. The results in Panel C provide strong evidence that innovations to the

[4] Note that equation (16) is equivalent to $\mathbb{E}\left[R^e_{i,t}\right] = \alpha_i + b^{\text{MKTRF}}\text{Cov}\left(R^e_{i,t}, \text{MKTRF}_t\right) + b^{\text{MACRO}}\text{Cov}\left(R^e_{i,t}, \text{MACRO}_t\right)$, where α_i is the average pricing error associated with the excess return ($R^e_{i,t}$) of test asset i, which is our focus in Panel C.

[5] While the two-factor model that includes shocks to the energy inflation rate (π^{Energy}) also produces a statistically insignificant pricing error, we note that (i) the pricing error is still economically large, (ii) the MAE of models that feature this shock are larger than the MAEs of the single-factor model, and (iii) the premium's exposure to this shock is statistically indistinguishable from zero, as discussed below. Thus, shocks to the energy inflation rate cannot explain the relative price premium.

aggregate degree of price dispersion help to reconcile the relative price premium. Notably, while Panels A and B show that innovations to price dispersion carry a negative market price of risk, Panel C shows that augmenting the CAPM with innovations to price dispersion renders the pricing error of the relative price premium insignificant. As a final piece of evidence that ties these facts together, we estimate the *exposure* of the relative price premium to the various macroeconomic shocks underlying Table 5.

The results in Panel D show that the relative price premium is *negatively* exposed to innovations in the cross-sectional dispersion of relative prices. Put differently, the returns of the relative price premium tend to be low when price dispersion increases. Combined with the negative market price of risk associated with the cross-sectional dispersion in relative prices, this result helps us to reconcile why the relative price premium arises. Notably, the premium arises because times of high price dispersion are "bad times" for investors (Panels A and B). As such, assets that negatively covary with price dispersion are risky due to their low returns in these bad states of the world. Given this risk, the representative investor demands a risk premium (i.e., a higher expected return) to hold these stocks. Finally, since the high RP-sorted portfolio has a lower covariance with aggregate price dispersion (Panel D), the high-minus-low RP-sorted portfolio's negative exposure to aggregate price dispersion risk translates into a high expected return for this portfolio, leading to the relative price premium.

4 Conclusion

This study examines the implications of relative price dispersion for asset prices. Our main empirical finding is that firms associated with goods and services that have increased in price by more than the headline inflation rate outperform firms associated with goods and services that have decreased in price by more than the inflation rate. The return spread between firms with high versus low relative price changes, which we refer to as the *relative price premium*, amounts to around 0.80% per month. This premium is not driven by changes in the level of inflation, is not explained by a host of common empirical asset-pricing factors and is immune to a battery of robustness checks.

We rationalize the relative price premium via a consumption-based asset-pricing model with multiple imperfectly substitutable goods and a representative investor who prefers to consume a balanced mix of the available goods. In the most general setting, we show that the representative agent is averse to changes in the distribution of relative prices so long as they possess a strictly concave utility function over consumption. We then illustrate how these shocks to price dispersion affect the agent's marginal utility in the context of a workhorse asset-pricing model with constant relative risk aversion preferences and a constant elasticity of substitution aggregator across two distinct goods. The model's key prediction is that periods of high price dispersion reflect states of the world in which the investor is unable to consume their preferred mix of the available goods. As a result, periods of high relative price dispersion signal bad times for the investor and the economy.

We empirically verify the model's prediction that high relative price dispersion signals bad times for the economy in two ways. First, we estimate the market price of risk associated with aggregate relative price dispersion via GMM and find that innovations to relative price dispersion carry a negative market price of risk. Second, we estimate a series of impulse response functions that show that a higher degree of relative price dispersion forecast contractions in key macroeconomic quantities, such as consumption, employment, and output. Put together, these two facts do indeed confirm that high relative price dispersion is bad for investors. Finally, we verify that shocks to the distribution of relative prices can explain the relative price premium, which has a negative covariance with these high price dispersion states. Thus, while a growing number of asset-pricing studies consider how assets prices respond to changes in the *level* of inflation, our study suggests that investors are also concerned about changes in the *dispersion* of relative prices.

References

Ait-Sahalia, Y., Parker, J. A., Yogo, M., 2004. Luxury goods and the equity premium. The Journal of Finance 59, 2959–3004.

Ang, A., Bekaert, G., 2007. Stock return predictability: Is it there? The Review of Financial Studies 20, 651–707.

Ang, A., Brière, M., Signori, O., 2012. Inflation and individual equities. Financial Analysts Journal 68, 36–55.

Ang, A., Chen, J., Xing, Y., 2006a. Downside risk. The review of financial studies 19, 1191–1239.

Ang, A., Hodrick, R. J., Xing, Y., Zhang, X., 2006b. The cross-section of volatility and expected returns. The journal of finance 61, 259–299.

Barnichon, R., Brownlees, C., 2019. Impulse response estimation by smooth local projections. Review of Economics and Statistics 101, 522–530.

Bekaert, G., Engstrom, E., 2010. Inflation and the stock market: Understanding the "fed model". Journal of Monetary Economics 57, 278–294.

Bhamra, H. S., Dorion, C., Jeanneret, A., Weber, M., 2022. High Inflation: Low Default Risk and Low Equity Valuations. The Review of Financial Studies Hhac021.

Bianchi, F., Lettau, M., Ludvigson, S. C., 2022. Monetary policy and asset valuation. The Journal of Finance 77, 967–1017.

Boons, M., Duarte, F., De Roon, F., Szymanowska, M., 2020. Time-varying inflation risk and stock returns. Journal of Financial Economics 136, 444–470.

Boudoukh, J., Richardson, M. P., Whitelaw, R., 1994. A tale of three schools: Insights on autocorrelations of short-horizon stock returns. Review of financial studies 7, 539–573.

Breeden, D. T., 1979. An intertemporal asset pricing model with stochastic consumption and investment opportunities. Journal of Financial Economics 7, 265–296.

Campbell, J. Y., Vuolteenaho, T., 2004. Inflation illusion and stock prices. American Economic Review 94, 19–23.

Carhart, M. M., 1997. On persistence in mutual fund performance. The Journal of finance 52, 57–82.

Chen, N.-F., Roll, R., Ross, S. A., 1986. Economic forces and the stock market. Journal of business pp. 383–403.

Cochrane, J. H., Longstaff, F. A., Santa-Clara, P., 2008. Two trees. The Review of Financial Studies 21, 347–385.

Cooper, I., Priestley, R., 2009. Time-varying risk premiums and the output gap. The Review of Financial Studies 22, 2801–2833.

Cooper, M. J., Gulen, H., Schill, M. J., 2008. Asset growth and the cross-section of stock returns. the Journal of Finance 63, 1609–1651.

Corhay, A., Kung, H., Schmid, L., 2020. Competition, markups, and predictable returns. The Review of Financial Studies 33, 5906–5939.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. The Journal of finance 52, 1035–1058.

De Loecker, J., Eeckhout, J., Unger, G., 2020. The rise of market power and the macroeconomic implications. The Quarterly Journal of Economics 135, 561–644.

Dittmar, R. F., Schlag, C., Thimme, J., 2020. Non-substitutable consumption growth risk. Available at SSRN 3289249 .

Eraker, B., Shaliastovich, I., Wang, W., 2016. Durable goods, inflation risk, and equilibrium asset prices. The Review of Financial Studies 29, 193–231.

Fama, E. F., 1981. Stock returns, real activity, inflation, and money. The American economic review 71, 545–565.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of financial economics 33, 3–56.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of financial economics 116, 1–22.

Fama, E. F., Schwert, G. W., 1977. Asset returns and inflation. Journal of financial economics 5, 115–146.

Fang, X., Liu, Y., Roussanov, N., 2022. Getting to the core: Inflation risks within and across asset classes. Tech. rep., National Bureau of Economic Research.

Ghysels, E., Horan, C., Moench, E., 2018. Forecasting through the rearview mirror: Data revisions and bond return predictability. The Review of Financial Studies 31, 678–714.

Gomes, J. F., Kogan, L., Yogo, M., 2009. Durability of output and expected stock returns. Journal of Political Economy 117, 941–986.

Gorodnichenko, Y., Weber, M., 2016. Are sticky prices costly? evidence from the stock market. American Economic Review 106, 165–99.

He, Z., Kelly, B., Manela, A., 2017. Intermediary asset pricing: New evidence from many asset classes. Journal of Financial Economics 126, 1–35.

Hoberg, G., Phillips, G., 2018. Conglomerate industry choice and product language. Management Science 64, 3735–3755.

Hodrick, R. J., 1992. Dividend yields and expected stock returns: Alternative procedures for inference and measurement. The Review of Financial Studies 5, 357–386.

Hou, K., Mo, H., Xue, C., Zhang, L., 2021. An augmented q-factor model with expected growth. Review of Finance 25, 1–41.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. The Journal of finance 45, 881–898.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of finance 48, 65–91.

Jordà, Ò., 2005. Estimation and inference of impulse responses by local projections. American economic review 95, 161–182.

Jump, R. C., Kohler, K., 2022. A history of aggregate demand and supply shocks for the united kingdom, 1900 to 2016. Explorations in Economic History 85, 101448.

Livnat, J., Mendenhall, R. R., 2006. Comparing the post–earnings announcement drift for surprises calculated from analyst and time series forecasts. Journal of accounting research 44, 177–205.

Lochstoer, L. A., 2009. Expected returns and the business cycle: Heterogeneous goods and time-varying risk aversion. The Review of Financial Studies 22, 5251–5294.

Lucas, R. E., 1978. Asset prices in an exchange economy. Econometrica: journal of the Econometric Society pp. 1429–1445.

Ludvigson, S. C., Ma, S., Ng, S., 2021. Uncertainty and business cycles: exogenous impulse or endogenous response? American Economic Journal: Macroeconomics 13, 369–410.

Martin, I., 2013. The lucas orchard. Econometrica 81, 55–111.

Moskowitz, T. J., Grinblatt, M., 1999. Do industries explain momentum? The Journal of finance 54, 1249–1290.

Newey, W. K., West, K. D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Novy-Marx, R., 2013. The other side of value: The gross profitability premium. Journal of financial economics 108, 1–28.

Pasten, E., Schoenle, R., Weber, M., 2020. The propagation of monetary policy shocks in a heterogeneous production economy. Journal of Monetary Economics 116, 1–22.

Pástor, L., Stambaugh, R. F., 2003. Liquidity risk and expected stock returns. Journal of Political economy 111, 642–685.

Shapiro, A. H., 2022. Decomposing supply and demand driven inflation. Federal Reserve Bank of San Francisco San Francisco.

Weber, M., 2015. Nominal rigidities and asset pricing. Available at SSRN 2478500 .

Yogo, M., 2006. A consumption-based explanation of expected stock returns. The Journal of Finance 61, 539–580.

Figures and Tables

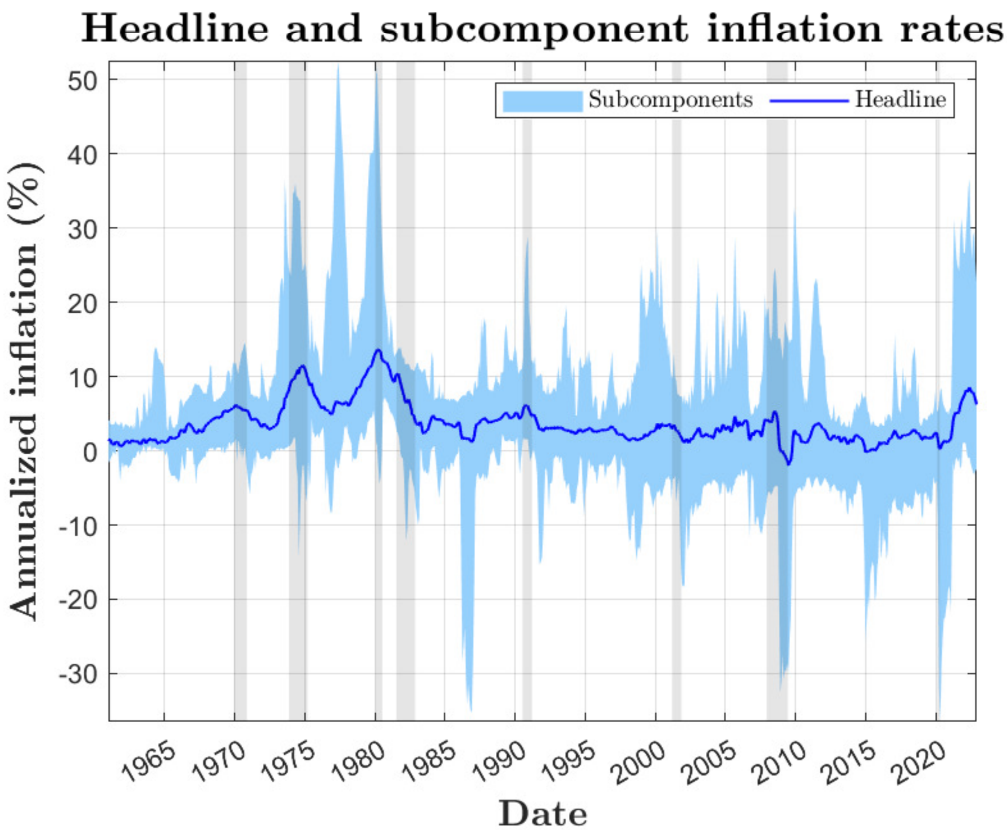
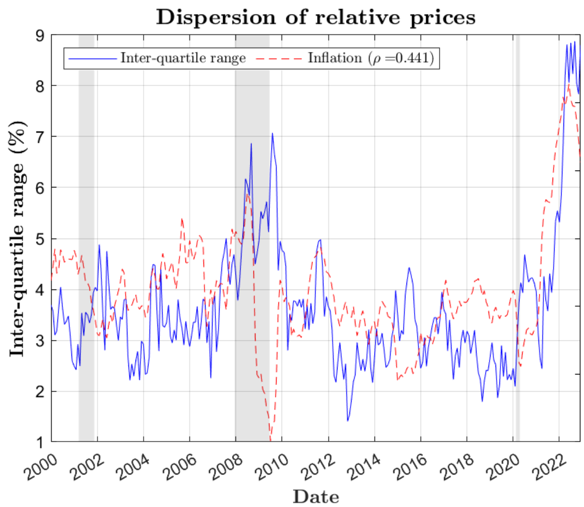
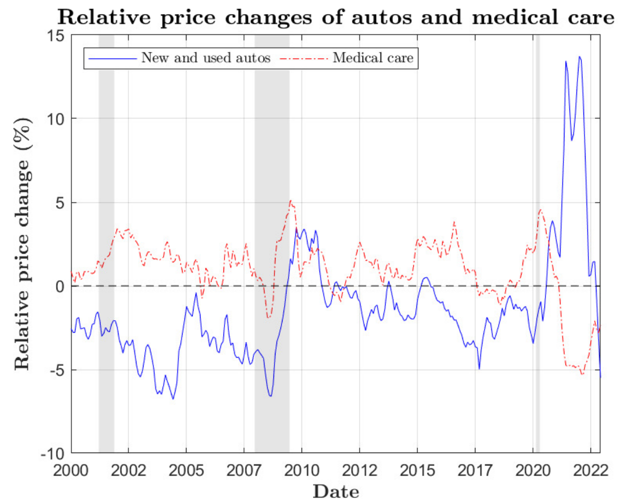


Figure 1: Headline CPI and the dispersion of its subcomponents
The figure displays the annualized headline inflation rate (solid blue line) and the cross-sectional dispersion of the annual growth rates of the subcomponents of headline CPI (light blue shaded region). Here, all annual growth rates are measured using the 12-month logarithmic change in headline CPI or its subcomponents. The cross-sectional dispersion in CPI is computed as the difference between the 97.5^{th} and 2.5^{th} percentile of the annual growth rates of the subcomponents of CPI. Data ranges from January 1961 to December 2022 and NBER recessions are denoted by light gray bars.



(a) Dispersion in relative price changes



(b) Relative price changes for two goods

Figure 2: Relative price changes over time

The figure shows the dispersion of relative prices over time across all sub-components of the headline CPI in our sample (Panel A) and relative price changes associated with two specific goods and services in our sample (Panel B). Specifically, Panel A reports the monthly time series of the cross-sectional in these relative prices, obtained via computing the inter-quartile range of relative price changes that are defined in accordance with equation (1). In computing these relative price changes, we set τ in this equation equal to 12 and plot the resulting inter-quartile range as the solid blue line. The same panel also plots the headline inflation rate as the dashed red line. Panel B then reports these relative price changes for two goods and services in our sample: new and used motor vehicles (solid blue line) and medical care (dashed red line). The data underlying this figure spans January 2000 to December 2022.

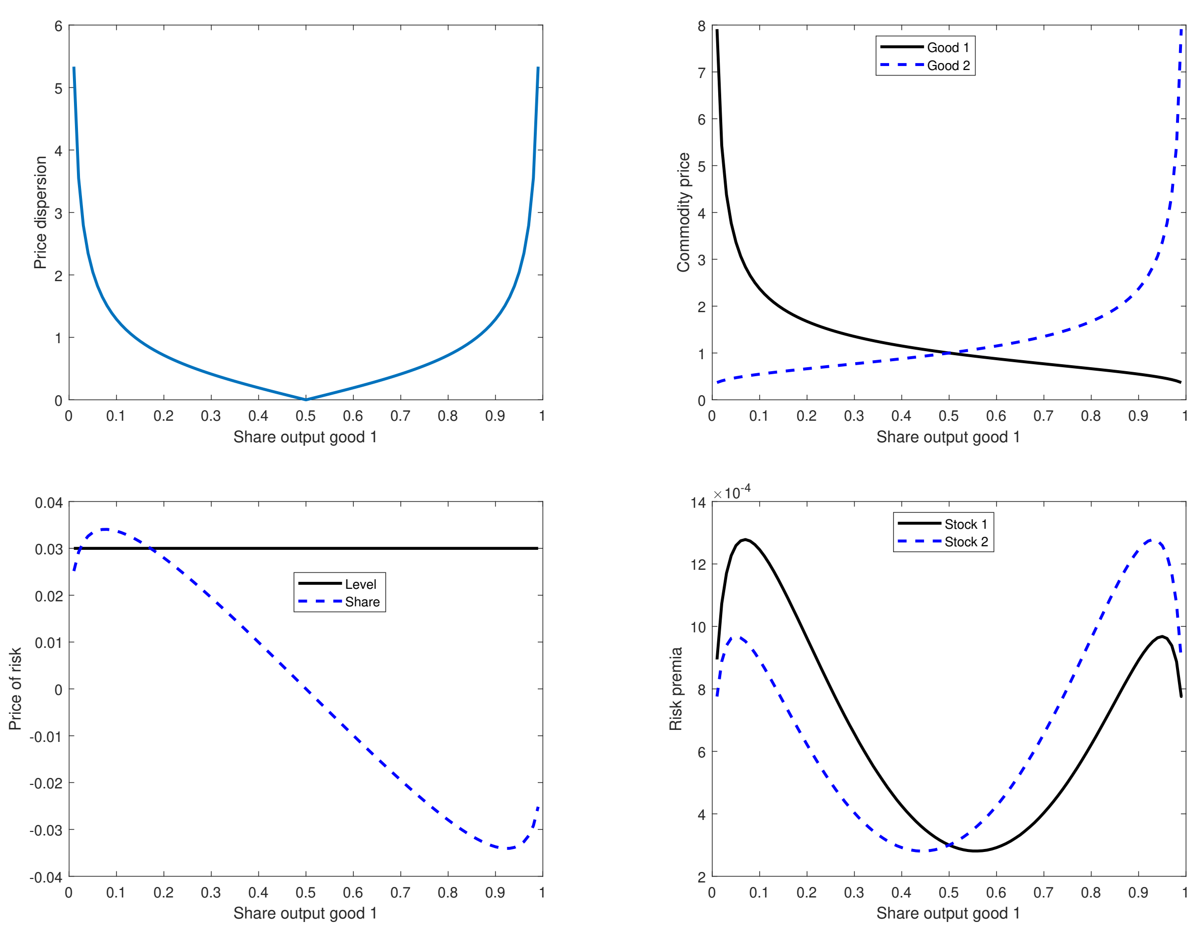


Figure 3: Price dispersion, commodity prices, the price of risk and risk premia
The top left panel shows the price dispersion measured as the cross-sectional standard deviation when using aggregate consumption, $\hat{C}$, as numeraire. The top right panel shows the price of good one (solid black line) and good two (dashed blue line). The bottom left panel shows the market price of risk associated with shocks to the level of consumption (solid black line) and shocks to the reallocative process (dashed blue line). The bottom right panel shows the risk premium on stocks one and two, computed using the definitions provided in Proposition 5 . Each figure varies the output share of good one along the x-axis. We use the following parameters: $\gamma = 3$, $\eta = 1.5$, $\alpha = 0.5$, $\mu = 0.02$, $\sigma_c = 0.01$, $\sigma_s = 0.05$, $\kappa = 0.01$, and $\bar{s} = 0.5$.

Table 1: Portfolios sorted on relative price changes

The table reports the average monthly returns of portfolios sorted on the relative price changes (RP) from equation (1) and the spread between the returns of the low and high RP-sorted portfolios. In each month t from December 1999 to November 2022, the relative price portfolios are formed such that the low (high) RP portfolio includes all price indexes with relative price changes above (below) the 10^{th} (90^{th}) percentile of the cross-sectional distribution of relative price changes in month $t-1$, subject to the requirement that a minimum of 30 firms are included in each price index. Each portfolio is then held for three months, resulting in a monthly time-series of overlapping portfolio returns that ranges from January 2000 to December 2022. Here, $\mathbb{E}[R]$ and $\sigma(R)$ denote the mean and standard deviation of the value-weighted returns associated with each portfolio. N(Firms) represents the average number of firms included in each relative price portfolio. $\mathbb{E}\left[R^{EW}\right]$ denotes each portfolio's average equal-weighted return, $\mathbb{E}\left[R^{Ind}\right]$ denotes each portfolio's average industry-adjusted return, while $\mathbb{E}\left[R^{DGTW}\right]$ reports each portfolio's average characteristic-adjusted return. We industry-adjust returns by subtracting the relevant Fama-French 12 industry return from each firm's individual stock return prior to conducting the portfolio sorts. Likewise, we characteristic-adjust returns by subtracting the return of the appropriate Daniel et al. (1997) benchmark return from each firm's individual stock return. Finally, parentheses report Newey and West (1987) robust t-statistics.

	$E[R]$	$\sigma(R)$	N(Firms)	$E\left[R^{\text{EW}}\right]$	$E\left[R^{\text{Ind}}\right]$	$E\left[R^{\text{DGTW}}\right]$
Low (L)	0.26	6.07	170	0.33	-0.31	-0.33
Medium	0.84	4.69	898	1.06	-0.15	0.04
High (H)	1.14	5.17	134	1.09	0.23	0.20
Spread	0.88	5.01		0.76	0.54	0.54
(H-L)	(3.27)			(2.70)	(2.38)	(2.44)

Table 2: Portfolio α's

This table reports the results of regressions of the relative price premium (i.e., the value-weighted returns of the portfolio that buys firms associated with high relative price changes and sells firms associated with low relative price changes) on common unconditional asset-pricing factors. Here, parameter estimates are obtained by regressing monthly excess returns on each set of monthly factors. MKTRF is the excess return of the market portfolio. SMB and HML are the size and value factors of the Fama and French (1993), while UMD is the momentum factor of Carhart (1997). Profit. and Invest. correspond to RMW and CMA factors (ROE and I/A factors) of the Fama and French (2015) five-factor model (Hou et al. (2021) q^t model). Lastly, EG represents the expected growth factor from Hou et al. (2021) q^5 model. Parentheses report Newey and West (1987) robust t-statistics. Returns span January 2000 to December 2022.

	(1)	(2)	(3)	(4)	(5)	(6)
	CAPM	FF3F	FF4F	FF5F	FF6F	q^5
α	1.03	0.99	0.89	0.94	0.90	0.71
	(4.02)	(3.64)	(3.18)	(3.32)	(3.19)	(2.13)
MKTRF	-0.31	-0.30	-0.21	-0.28	-0.21	-0.21
	(-3.39)	(-3.49)	(-2.31)	(-3.44)	(-2.50)	(-2.30)
Size		-0.06	-0.09	-0.06	-0.11	0.06
		(-0.61)	(-0.90)	(-0.49)	(-0.84)	(0.48)
HML		0.21	0.27	0.16	0.27	
		(1.50)	(2.02)	(0.87)	(1.50)	
UMD			0.20		0.20	
			(1.86)		(-0.36)	
Profit.				-0.02	-0.06	0.21
				(-0.09)	(-0.36)	(1.27)
Invest.				0.17	0.08	0.39
				(0.72)	(0.37)	(2.51)
EG						0.53
						(0.20)
$\bar{R}^2$	8.07	9.88	13.09	9.52	12.52	11.70

Table 3: Portfolio characteristics

The table reports the value-weighted characteristics of the portfolios sorted on relative price changes (i.e., RP from equation (1)). All data is recorded at the end of each portfolio formation month from December 1999 to November 2022 and the details on the construction of each variable are provided in Section A.1 of the Online Appendix. The column Spread(H-L) refers to the difference between the average characteristics of the low and high RP-sorted portfolios, and t(Spread) is the Newey and West (1987) t-statistic associated with this difference.

	Low (L)	Medium	High (H)	Spread (H-L)	t(Spread)
Panel A: Accounting and return-based characteristics					
ln(ME)	6.34	6.32	6.54	0.20	(2.87)
ln(BEME)	-0.71	-0.69	-0.69	0.02	(0.41)
Asset growth (%)	2.75	2.31	3.23	0.48	(1.22)
Gross profitability (%)	9.50	8.78	6.70	-2.80	(-4.84)
IVOL (%)	2.54	2.54	2.44	-0.10	(-1.42)
Prior month return (%)	0.82	0.83	1.41	0.58	(1.71)
Momentum (%)	16.22	15.54	20.84	4.62	(1.87)
HHI	10.21	12.62	8.51	-1.70	(-1.60)
Markup	1.03	1.04	0.99	-0.04	(-1.63)
Price rigidity	0.25	0.22	0.26	0.01	(0.10)
SUE1 (%)	0.05	0.07	0.23	0.18	(0.91)
SUE2 (%)	0.02	0.11	0.20	0.18	(1.15)
SUE3 (%)	0.00	-0.02	-0.03	-0.03	(-1.38)
Panel B: Inflation betas					
β^{BDRS}	0.77	0.31	0.63	-0.14	(-0.77)
β^{Headline}	1.29	1.13	0.82	-0.47	(-2.35)
β^{Core}	1.59	1.01	-0.39	-1.99	(-2.74)
β^{Energy}	0.13	0.13	0.12	-0.01	(-0.82)
β^{Food}	0.73	0.28	0.60	-0.14	(-0.63)

Table 4: Independence from inflation- and durability-related spreads
This table documents the independence of the relative price premium (i.e., the value-weighted returns of the portfolio that buys high RP stocks and sells low RP stocks) from a number of spreads related to the level of inflation and asset durability. In particular, we look at the extent to which the relative price premium is linearly related to the inflation spread of Boons et al. (2020), spreads based on firms' exposures to each of headline inflation (π^{Headline}), core inflation (π^{Core}), and energy inflation (π^{Energy}), motivated by Fang et al. (2022), and the asset durability spread of Gomes et al. (2009). Details on the construction of the inflation betas underlying each spread are provided in Section A.1 of the Online Appendix. We implement this analysis by projecting the returns of the relative price premium on the returns associated with each of the aforementioned spreads and record the resulting intercepts (alphas). Parenthesis report t-statistics computed using Newey and West (1987) standard errors. Finally, returns span January 2000 to December 2022.

	(1)	(2)	(3)	(4)	(5)
α	0.87	0.92	0.88	0.88	0.87
	(3.23)	(3.43)	(3.28)	(3.28)	(3.26)
$\pi^{\text{Boons et al.}}$	-0.12				
	(-1.19)				
π^{Headline}		-0.09			
		(-1.47)			
π^{Core}			-0.01		
			(-0.36)		
π^{Energy}				-0.08	
				(-1.40)	
Durability					0.10
					(0.72)
$\bar{R}^2$	1.14	0.95	-0.32	0.83	-0.09

Table 5: Pricing the relative price portfolios using macroeconomic variables

The table reports statistics related to the ability of different macroeconomic shocks to price the RP-sorted portfolios. We posit that the SDF is given by equation (7) and is driven by the market's excess return ($MKTRF_t$) and an additional macroeconomic shock ($MACRO_t$). The macroeconomic shocks we focus on are innovations to the (i) cross-sectional dispersion of relative prices, measured using the inter-quartile range of relative prices from equation (1) (ΔRP), (ii) the corporate default spread (DEF), (iii) macroeconomic uncertainty from Ludvigson et al. (2021) (UNC), (iv) the liquidity factor from Pástor and Stambaugh (2003) (LIQ), (v) intermediary capital from He et al. (2017), and in the spirit of Fang et al. (2022), shocks to (vi) core inflation (π^{Core}) and (vii) energy inflation (π^{Energy}). We use GMM to estimate equation (15) using five RP-sorted portfolios constructed following the procedure in Section 2.1. Panel A reports the market prices of risk associated with $MKTRF_t$ and $MACRO_t$ when the test assets are the RP-sorted portfolios, whereas Panel B reports the same quantities when we use a broader set of test assets that features the Fama-French five industry portfolios, six portfolios sorted on size and book-to-market, six portfolios sorted on size and momentum, and six portfolios sorted on size and investment. Panel C reports model-implied pricing error (α) associated with the relative price premium. Finally, panel D reports the covariances between the returns of the relative price premium and (i) excess market returns and (ii) each macroeconomic shocks. We compute these covariances using the backward-looking moving average of each macroeconomic shock. The sample underlying this table spans from January 2000 to December 2022 and parentheses report Newey and West (1987) robust t-statistics.

	MKTRF	ΔRP	DEF	UNC	LIQ	INT	π^{Core}	π^{Energy}
Panel A: Market price of risk among RP-sorted portfolios								
λ_{MKTRF}	0.16	0.29	0.32	0.34	0.25	-0.99	0.15	-0.07
	(2.13)	(1.62)	(3.18)	(3.35)	(2.41)	(-1.74)	(1.61)	(-0.19)
λ_{MACRO}		-2.39	0.73	0.76	-0.72	1.47	-1.17	2.60
		(-1.71)	(2.18)	(2.15)	(-2.52)	(1.89)	(-2.78)	(0.89)
MAE	0.20	0.12	0.21	0.23	0.18	0.15	0.16	0.22
Panel B: Market price of risk among broader test assets								
λ_{MKTRF}	0.26	0.22	0.27	0.20	0.30	0.40	0.13	0.15
	(4.45)	(4.77)	(5.53)	(3.12)	(4.98)	(4.43)	(2.55)	(1.90)
λ_{MACRO}		-0.69	0.57	-0.26	-0.21	-0.22	-0.49	1.10
		(-6.00)	(6.60)	(-1.77)	(-2.84)	(-2.21)	(-3.72)	(5.25)
MAE	0.62	0.36	0.21	0.63	0.63	0.46	0.18	0.68
Panel C: Pricing errors								
Low (L)	-0.51	-0.29	-0.46	-0.25	-0.07	-0.28	-0.44	-0.31
Medium	0.34	-0.03	0.19	0.19	0.52	0.23	-0.09	0.33
High (H)	0.34	-0.03	0.19	0.19	0.52	0.23	-0.09	0.33
Spread	0.84	0.26	0.65	0.44	0.59	0.51	0.35	0.63
(H-L)	(3.98)	(1.29)	(2.80)	(4.51)	(2.52)	(1.93)	(3.24)	(1.35)
Panel D: Covariances								
Cov(MKTRF)	-1.17	-0.85	-0.78	-0.80	-0.83	-0.85	-0.83	-0.82
(H-L)	(-3.75)	(-3.94)	(-3.78)	(-3.84)	(-3.90)	(-3.95)	(-3.91)	(-3.87)
Cov(Macro)		-0.30	0.40	0.70	-0.31	-0.53	-0.39	0.05
(H-L)		(-2.11)	(1.91)	(2.30)	(-1.65)	(-2.40)	(-2.00)	(0.24)

A Online Appendix

A.1 Variable description and construction

Size. The market value of a firm at time t is computed as the product of the firm's share price (CRSP Monthly item PRC) multiplied by the number of shares outstanding (CRSP Monthly item SHROUT). This quantity is then scaled to express the market value of equity of each firm in millions of dollars.

BEME. The book-to-market ratio is computed as the book value of a firm's equity in quarter t, scaled by the market value of the firm's equity in quarter $t-1$. Here, we define the book equity as either (i) shareholder's equity (Compustat Quarterly item SEQQ), (ii) common equity (Compustat Quarterly item CEQQ) plus the value of preferred equity (Compustat Quarterly item PSTKQ), or (iii) the difference in total assets (Compustat Quarterly item ATQ) and total liabilities (Compustat Quarterly item LTQ), in that order of preference. We add the value of deferred taxes and investment tax credits (Compustat Quarterly item TXDITCQ) to the value of shareholder equity (setting this item equal to zero in cases in which it is not available), and we subtracted the value of preferred equity from the resulting figure.

Quarterly asset growth. The quarterly asset growth rate is computed as the change in total assets (Compustat Quarterly item ATQ) between fiscal quarter t and $t-1$.

Annual asset growth. The annual asset growth rate is computed as the change in total assets (Compustat Quarterly item ATQ) between fiscal quarter t and $t-4$.

Gross profitability. Gross profitability is computed as the difference between revenue (Compustat Quarterly item REVTQ) and cost of goods sold (Compustat Quarterly item COGSQ) in fiscal quarter t, scaled by the total assets (Compustat Quarterly item ATQ) in quarter $t-1$.

HHI. The Herfindahl–Hirschman index associated with each firm i is constructed by computing the firm's squared market share relative to peer firms assigned to the same BLS price index. Here, market share is define as the firm's sales (Compustat Quarterly item SALEQ) scaled by the sum of the sales of the firm's peers.

Industry momentum. Industry momentum is constructed following the basic procedure outlined by Moskowitz and Grinblatt (1999). That is, each firm is assigned to an industry on the basis of its two-digit SIC code. After computing the value-weighted returns associated with each industry index, we calculate each industry's stock return momentum at each time t using the industry's returns over the previous $t-11$ to $t-1$ months. Finally, we take the difference in returns between the three "winner" and "loser" industries to compute industry momentum at time t.

IVOL. Idiosyncratic volatility is computed by following Ang et al. (2006b). Specifically, at the end of each month t, a firm's idiosyncratic volatility over the previous month is obtained by regressing the stocks excess daily returns on the data Fama and French (1993) factors, provided there are at least 15 valid daily returns in the month. Idiosyncratic volatility is then defined as the standard deviation of the residuals from the aforementioned regression.

Markup. Firm-level markups are estimated using production-function approach described by De Loecker et al. (2020).

Momentum. The stock return momentum of firm i in month t is defined as the firm's cumulative return between months $t-11$ and $t-1$. This measure is constructed using CRSP Monthly return data that is adjusted for de-listing events.

Price rigidity. We obtain the measure of price rigidity from Pasten et al. (2020). The measure is based on the frequency of good-level price changes, as recorded by BLS, aggregated to the industry-level. As this data is available at varying degrees of granularity, we map the price rigidity measure to firms by first matching on six-digit NAICS codes. For any unmatched firms, we then proceed to match on five-digit NAICS codes. We repeat this process for four-, three-, and two-digit NAICS codes, respectively. This ensures that all firms are matched to the most granular measure of price rigidity available.[6]

Prior month return. The prior month return of firm i at time t is defined as the the firm's total return in month $t-1$ (CRSP Monthly item RET).

SUE1. Following Livnat and Mendenhall (2006), SUE1 in quarter t is the difference between split-adjusted earnings per share excluding extraordinary items (Compustat Quarterly item EPSPXQ divided by item AJEXQ) in quarters t and $t-4$, scaled by the split-adjusted price at the end of quarter t (Compustat Quarterly item PRCCQ divided by item AJEXQ).

SUE2. Following Livnat and Mendenhall (2006), SUE2 in quarter t is the difference between split-adjusted earnings per share excluding both extraordinary items and special items (Compustat

[6] We thank Michael Weber for making this data available on his website at the following link: https://faculty.chicagobooth.edu/michael-weber/research/data.

Quarterly item EPSPXQ minus 65% of item SPIQ scaled by item CSHPRQ, all divided by item AJEXQ) in quarters t and $t-4$. This difference is then scaled by the split-adjusted price at the end of quarter t (Compustat Quarterly item PRCCQ divided by item AJEXQ).

SUE3. Following Livnat and Mendenhall (2006), SUE3 in quarter t is the difference between actual EPS from the I/B/E/S unadjusted files and the median analyst forecast of EPS for the same point in time (I/B/E/S Unadjusted item MEDEST). This difference is then scaled by the share price on the release date (I/B/E/S Unadjusted item PRICE).

β^{BDRS}. Following Boons et al. (2020), we obtain each firm's exposure to headline inflation rate in month t by regressing each firm's excess stock returns on innovations to inflation over a recursive window that spans at least the past 24 months. Here, innovations to the headline inflation rate are obtained by filtering inflation though an ARMA(1,1) model and observations are weighted such that the more recent returns and innovations influence the estimated exposure more than distant returns and innovations. Finally, we adjusted the estimated exposures to account for the effects of estimation error. See equation (4), (5), and (6) and the surrounding discussion in Boons et al. (2020) for full details.

β^{Headline}. In the spirit of Fang et al. (2022), we obtain the unexpected component of the headline inflation rate by estimating a monthly VAR that not only includes the headline, core, food, and energy inflation rates, but also includes the risk-free rate, corporate default spread, excess market returns, and the output gap. Full details on this estimation are provided in Section A.3. The exposure of firm i at time t is then estimated over a rolling window that includes the past 60 months of returns, provided that at least 24 months of returns are available.

β^{Core}. In the spirit of Fang et al. (2022), we obtain the unexpected component of the headline inflation rate by estimating a monthly VAR that not only includes the headline, core, food, and energy inflation rates, but also includes the risk-free rate, corporate default spread, excess market returns, and the output gap. Full details on this estimation are provided in Section A.3. The exposure of firm i at time t is then estimated over a rolling window that includes the past 60 months of returns, provided that at least 24 months of returns are available.

β^{Energy}. In the spirit of Fang et al. (2022), we obtain the unexpected component of the headline inflation rate by estimating a monthly VAR that not only includes the headline, core, food, and energy inflation rates, but also includes the risk-free rate, corporate default spread, excess market returns, and the output gap. Full details on this estimation are provided in Section A.3. The exposure of firm i at time t is then estimated over a rolling window that includes the past 60 months of returns, provided that at least 24 months of returns are available.

$\boldsymbol{\beta}^{\mathbf{Food}}$**.** In the spirit of Fang et al. (2022), we obtain the unexpected component of the headline inflation rate by estimating a monthly VAR that not only includes the headline, core, food, and energy inflation rates, but also includes the risk-free rate, corporate default spread, excess market returns, and the output gap. Full details on this estimation are provided in Section A.3. The exposure of firm i at time t is then estimated over a rolling window that includes the past 60 months of returns, provided that at least 24 months of returns are available.

A.2 Relative price dispersion and the business cycle

The consumption-based asset-pricing model we propose in Section 3.1 indicates that shocks to the cross-sectional distribution of consumption is a relevant source of aggregate risk that affects marginal utility. In line with this prediction of the model, the analysis underlying Panels A and B of Table 5 shows that price dispersion risk is indeed priced in the cross section of asset returns and has a negative market price of risk. In other words, increases in relative price dispersion signal bad times for investors. Rather than relying on asset-pricing data to establish this fact, this section considers a complementary approach and asks whether increases in relative price dispersion predict declines in future macroeconomic growth.

We address this question by estimating a series of impulse response functions (IRFs) that examine how a one-time shock to relative price dispersion propagates to key business cycle variables. Specifically, we examine how increases in relative price dispersion predict four key macroeconomic variables: the monthly growth rates of industrial production, personal income, consumption, and the monthly change in the unemployment rate. We estimate these IRFs using the smooth local projection method of Barnichon and Brownlees (2019). These IRFs are based on a series of h-month ahead predictive regressions for $h \in \{1, \ldots, H\}$

$$y_{t+h} = \beta_{0(h)} + \beta_{1(h)} y_t + \beta_{2(h)} \Delta\pi_t + \sum_{p=1}^{P} \boldsymbol{\gamma}'_{p(h)} \boldsymbol{\Gamma}_{t-p} + \varepsilon_{t+h}, \tag{A.1}$$

where y_{t+h} represents one of four macroeconomic outcomes at time $t+h$, $\Delta\pi_t$ represents the inter-quartile range relative price changes at time t, and $\mathbf{\Gamma}_t$ is a matrix of controls that includes (i) an additional lag of both y_t and $\Delta\pi_t$, (ii) the level of the inflation rate, (iii) the term spread, (iii) the corporate default spread, and (iv) excess market returns. Unlike the local projection method of Jordà (2005), which entails running separate predictive regressions for each forecast horizon h, the smooth local projection method ensures that effects of a one-time shock to relative price dispersion (or any other macroeconomic variable of interest) evolve as smooth functions of the forecast horizon, as economic intuition suggests is the case. When estimating these figures, each variable is scaled so that the resulting IRFs can be interpreted as the effects of a one-standard deviation increase in relative price dispersion.

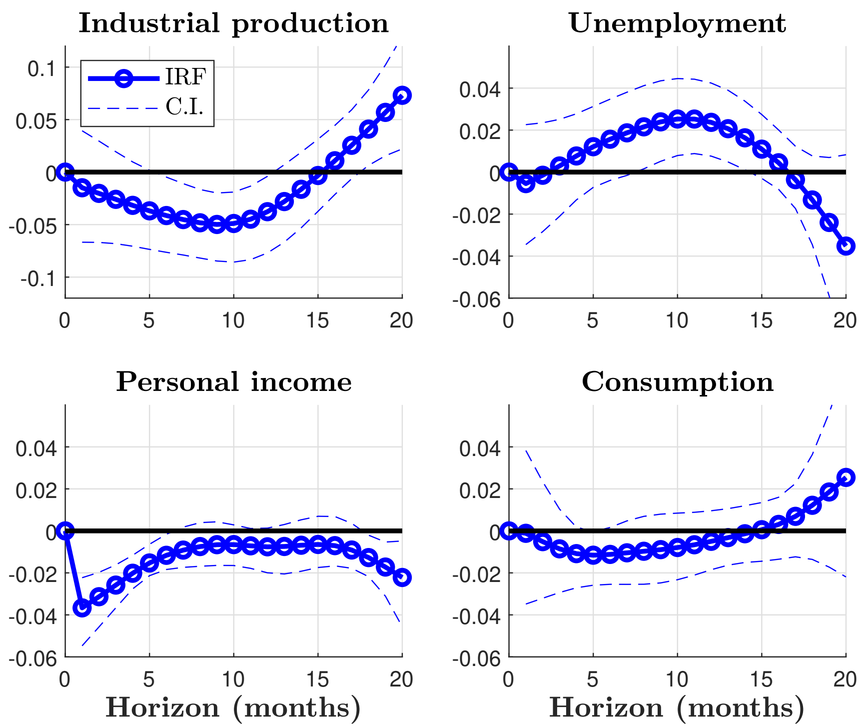


Figure A.1: Impulse response functions
The figure displays impulse response functions (IRFs) that demonstrate how a one-standard deviation change in the cross-sectional distribution of relative price changes predicts the monthly growth rate of industrial production (top left), the monthly change in the unemployment rate (top right), the monthly growth rate of real personal income (bottom left), and the monthly growth rate of real consumption (bottom right). These IRFs are estimated following equation A.1, which is based on the smooth local projection method of Barnichon and Brownlees (2019). The time series underlying this analysis ranges from January 1970 to December 2022.

Figure A.1 shows that, consistent with the asset-pricing results in Table 5, increases in relative price dispersion predict macroeconomic contractions (i.e., signal bad times for the economy and investors). For instance, the top left (bottom left) panel indicates that output (personal income) falls by roughly 0.05 (0.03) standard deviations after a one-standard deviation increase in relative price dispersion, conditional on the comprehensive set of controls included in equation (A.1). Likewise, unemployment tends to rise and consumption tends to fall after price dispersion increases. This supports the notion that high price dispersion states are bad states of the world, at least from the perspective of an economic agent with recursive utility and a preference for the early resolution of uncertainty.

A.3 Estimating inflation shocks

In the spirit of Fang et al. (2022), we extract innovations to headline, core, food, and energy inflation via the following VAR that is estimated using monthly data

$$\boldsymbol{Y}_t = \boldsymbol{c} + \boldsymbol{\Gamma}\boldsymbol{Y}_{t-1} + \boldsymbol{\varepsilon}_t. \tag{A.2}$$

Here, $\boldsymbol{Y}_t$ is a vector that includes the time-t values of the headline, core, food, and energy inflation rates, as well as the monthly risk-free rate, excess market returns, corporate default spread, and output gap. As we implement the VAR represented by equation (A.2) with monthly data that spans January 1980 to December 2022, we measure the output gap by following the approach of Cooper and Priestley (2009). That is, we run the following regression

$$\ln(IP_t) = \beta_0 + \beta_1 \times t + \beta_2 \times t^2 + \psi_t,$$

where IP_t is the value of the industrial production index at time t, and t (t^2) represents a linear (quadratic) time trend. The residual, ψ_t, then reflects the output gap at time t. Consequently, the unexpected component of headline, core, food, and energy inflation is then the first, second, third, and fourth component of the vector $\boldsymbol{\varepsilon}_t$.

A.4 Estimating elasticity of substitution in equation (3)

As explained in Section 3, we assume that goods one and two in equation (3) are substitutes. This subsection provides empirical evidence in support of this assumption by estimating the elasticity of substitution η between bundles of goods underlying the CPI. Our null hypothesis is that $\eta \leq 1$, which implies either a Cobb-Douglas aggregator (if $\eta = 1$) or complementarity between goods (if $0 \leq \eta < 1$). A rejection of this null, thus, implies that $\eta > 1$ and goods are substitutes. In what follows, we show that this null hypothesis is rejected.

Our objective is to estimate the average elasticity of substitution (η) across bundles. We follow the approach outlined in Dittmar et al. (2020), exploiting the well-known fact that a consumer's intratemporal marginal rate of substitution (IMRS) between two goods is equal to the relative price of the two goods, provided that the consumer is subject to a budget constraint.

To estimate the elasticity of substitution between arbitrary goods, we start with a CES aggregator of M distinct bundles of goods,

$$\hat{C}_t = \left[\sum_{i=1}^{M} a_{i,t} B_{i,t}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \tag{A.3}$$

where η is the elasticity of substitution between bundles. Instead of looking at single goods, we are interested in estimating the elasticity of substitutability between bundles of goods, $B_{i,t}$, that closely mimic the CPI indices used in our main results. The specification in equation (A.3) implies that all individual goods within each bundle are perfect substitutes. That is, $B_{i,t}$ is a linear combination of the quantities of specific consumption goods within the bundle. $a_{i,t}$ is a share for each bundle such that $a_{i,t} > 0$ for all i = 1, …, M, and $\sum_{i=1}^{M} a_{i,t} = 1$.

The IMRS between two bundles k and j is given as

$$\text{IMRS} = \frac{\partial \hat{C}_t / \partial \hat{B}_{k,t}}{\partial \hat{C}_t / \partial \hat{B}_{j,t}} = \frac{a_{k,t} B_{k,t}^{-\frac{1}{\eta}}}{a_{j,t} B_{j,t}^{-\frac{1}{\eta}}}, \tag{A.4}$$

where $B_{k,t}$ and $B_{j,t}$ are two different bundles of consumption goods. The IMRS between the two bundles then equals the relative prices of these bundles:

$$\frac{a_{k,t} B_{k,t}^{-\frac{1}{\eta}}}{a_{j,t} B_{j,t}^{-\frac{1}{\eta}}} = \frac{P_{k,t}}{P_{j,t}}. \tag{A.5}$$

Applying the logarithm to each term of the equation (A.5), we obtain:

$$(\log P_{k,t} - \log P_{j,t}) + \frac{1}{\eta}(\log B_{k,t} - \log B_{j,t}) + (\log a_{j,t} - \log a_{k,t}) = \epsilon_{k,j,t}. \tag{A.6}$$

Our goal is then to test the the null hypothesis described above (i.e., that $\eta \leq 1$ or, equivalently, that $\frac{1}{\eta} \geq 1$) by estimating the slope coefficient associated with the $(\log B_{k,t} - \log B_{j,t})$ term in equation (A.6). Motivated by Yogo (2006), we assume that $(\log a_{j,t} - \log a_{k,t})$ remains constant across time periods and is estimated below as a bundle-pair fixed effect. As we highlight and describe below, the null hypothesis that $\frac{1}{\eta} \geq 1$ is rejected for the pairs of consumption bundles underlying our empirical results. This suggests that $\frac{1}{\eta} < 1$ and indicates that the assumption of substitutability made in Section 3 is valid.

We test equation (A.6) using yearly data from BEA's National Income and Product Accounts (NIPA) that covers the period from 2000 to 2022. The indexes k and j are associated with various types of consumption goods. To be consistent with the baseline portfolio formation procedure, we exclude indexes that are (i) very granular in nature and not available in NIPA (e.g. prices for bakery goods, dairy, and sweets) and (ii) very coarse in nature (e.g. the for medical care, since we have indexes for medical care product and medical services). Table A.1 presents a comprehensive list of the twenty six consumption indexes we consider. The table also provides the connection between the BLS consumption indexes and the bundles represented in the NIPA data. We use this data to estimate equation (A.6) and obtain inverse elasticity of substitution between all pairs of the twenty six consumption bundles k and j described above. This results in a total of three hundred and twenty five combinations of distinct consumption bundles.

In the data, we use NIPA price indices (Table 2.4.4) as a stand in for $\log P_{k,t} - \log P_{j,t}$. The base year is 2012 such that the relative price between all pairs of goods is one in this specific year. As in Dittmar et al. (2020), we then define bundles $B_{k,t}$ and $B_{j,t}$ in equation (A.6) as the NIPA quantity indices (Table 2.4.3) in year t multiplied by the NIPA nominal expenditures (Table 2.4.5) in the base year divided by the total population in year t (Table 7.1). Having constructed empirical proxies for $B_{k,t}$ and $B_{j,t}$, we estimate the value of $\frac{1}{\eta}$ in equation (A.6) by employing a two-step

Table A.1: Link between the consumption indexes in NIPA and bundles from BLS
The table reports our link between the consumption indexes in the BEA's National Income and Product Accounts (NIPA) and the BLS's price indexes.

BLS ID	BLS Name	NIPA Name
CPIAPPSL	Apparel	Clothing and footwear
CUSR0000SAE21	Information	Communication
CPIFABSL	Food and beverages	Food and beverages purchased for off-premises consumption
CUSR0000SAF116	Alcohol	Alcoholic beverages purchased for off-premises consumption
CUSR0000SAG1	Personal care	Personal care products
CUSR0000SAH2	Fuels and Utilities	Fuel oil and other fuels
CUSR0000SAH3	Household	Household consumption expenditures
CUSR0000SAM1	Medical equipment	Pharmaceutical and other medical products
CUSR0000SAM2	Medical services	Outpatient services
CUSR0000SAT1	Private transportation	Motor vehicle services
CUSR0000SEAE	Footwear	Other clothing materials and footwear
CUSR0000SEEE	IT and hardware	Telecommunication services
CUSR0000SAF11	Food at home	Food & nonalcoholic beverages
CUSR0000SEFV	Restaurants	Purchased meals and beverages
CUSR0000SEGA	Tobacco	Tobacco
CUSR0000SEHB	Hotels	Accommodations
CUSR0000SERA	Video and Audio	Audio-video, photographic, and information processing equipment
CUSR0000SERE01	Toys	Recreational items
CUSR0000SERE03	Music	Musical instruments
CUSR0000SERF01	Clubs	Membership clubs, sports centers, parks, theaters, and museums
CUSR0000SETA	Vehicles	Motor vehicles and parts
CUSR0000SETB	Motor fuel	Motor vehicle fuels, lubricants, and fluids
CUSR0000SETC	Vehicle parts	Motor vehicle parts and accessories
CUSR0000SETD	Vehicle maintenance	Motor vehicle maintenance and repair
CUSR0000SETG	Public transportation	Public transportation
CUSR0000SETG01	Airfares	Air transportation

GMM method. The moment conditions underlying this estimator are

$$E_t \begin{bmatrix} \epsilon_{1,2,t} \\ \epsilon_{1,2,t}(\log P_{1,t} - \log P_{2,t}) \\ \epsilon_{1,3,t} \\ \epsilon_{1,3,t}(\log P_{1,t} - \log P_{3,t}) \\ \dots \\ \epsilon_{25,26,t} \\ \epsilon_{25,26,t}(\log P_{25,t} - \log P_{26,t}) \end{bmatrix} = \mathbf{0}, \tag{A.7}$$

such that each bundle-pair has two moment conditions—one capturing the unconditional and the other the conditional errors of equation (A.6). The first step of the GMM estimator places an equal weight on all moment conditions by using the identity matrix as the weighting matrix, while the second step of the estimation procedure uses a weighting matrix based on the Newey and West (1987) covariance matrix.

This GMM estimator shows that the inverse of the elasticity of substitution, or $\frac{1}{\eta}$ in equation (A.6), is less than one for the average pair of goods we consider. Table A.2 presents these results by showing the average value of $\frac{1}{\eta}$ across all pairs of consumption indexes. The average value of $\frac{1}{\eta}$ across all pairs of indexes is 0.623. Additionally, we conduct a Wald test on the null hypothesis that $\frac{1}{\eta} \geq 1$. The Wald test statistic is 4.037 and the corresponding p value is 0.044. This means that we reject the null hypothesis that $\frac{1}{\eta} \geq 1$ at the 5% level of statistical significance, implying that $\frac{1}{\eta} < 1$. Once again, these findings lend empirical support to our assumption that goods across consumption indexes are substitutes.

Table A.2: Average elasticity of substitution (η)
The table reports the average elasticity of substitution (η) underlying equation (3). We estimate this elasticity of substitution by following the process outlined in Section A.4 of the Online Appendix to construct a GMM-based estimator of $\frac{1}{\eta}$ across all pairs of consumption indexes underlying our analysis and reported in Table A.1 of the Online Appendix. The moment conditions underlying this GMM estimator are represented by equation (A.7). The first stage of the estimation procedure employs the identify matrix to weight all moment conditions equally, whereas we use the Newey and West (1987) matrix as the weighting matrix in the second step of the estimation procedure. The table also presents the Wald statistic and the corresponding p-value associated with the null hypothesis that $\frac{1}{\eta} \geq 1$.

Statistic	**Value**
Average value of $\frac{1}{\eta}$	0.623
Wald statistic ($H_0 : \frac{1}{\eta} \geq 1$)	4.037
p-value	0.044

Table A.3: Dependent double sorting on the elasticity of substitution and relative price changes

The table reports the average monthly returns of portfolios sorted on the elasticity of substitution (η) in equation (3) and the relative price changes (RP) in equation (1). We report the spread between the returns of the low and high η- and low and high RP-sorted portfolios. In each month t from December 1999 to November 2022, the double-sorted portfolios are formed such that the high (low) η-and-RP portfolio includes all price indexes with RP above (below) the 10^{th} (90^{th}) percentile of the cross-sectional distribution of RP in month $t-1$, and η above (below) the median of the cross-sectional distribution of η, respectively. The portfolio formation is subject to the requirement that a minimum of 30 firms are included in each price index and elasticity bundle. We report the average spread between high-RP-high-η portfolio and low-RP-low-η portfolio. Each portfolio is then held for three months, resulting in a monthly time series of overlapping portfolio returns that ranges from January 2000 to December 2022. Here, $\mathbb{E}[R]$ and $\sigma(R)$ denote the mean and standard deviation of the value-weighted returns associated with each portfolio. Finally, parentheses report Newey and West (1987) robust t-statistics.

		Elasticity of substitution			
		Low (L)	High (H)	Low (L)	High (H)
		$E[R]$		$\sigma[R]$	
	Low (L)	0.64	0.70	6.27	5.95
RP	High (H)	0.94	1.33	5.10	4.49
	Spread		0.69		4.75
			(2.45)		

The relative price premium arises from the bundles with high elasticity rather than low elasticity. To formally test this, we do dependent double sorting on the elasticity of substitution and the relative price changes. That is, we first sort on the elasticity of substitution such that the high (low) η-portfolio includes all price indexes with η above (below) the median of the cross-sectional distribution of η. When sorting on η per each price index, we use the median η for the pairwise η's estimated in equation (A.6) for all pairs of price indexes shown in Table A.1. Then, within these buckets, we sort on relative price changes using 10^{th} and 90^{th} percentile breakpoints. For example, high-η and low-RP portfolio has all price indexes with η above the median of the cross-sectional distribution of η, and within this bucket, the price indexes with the top decile of RP.

A.5 Disentangling supply- and demand-driven price changes

This section uses the methodology proposed by Shapiro (2022) to attribute the price changes underlying our analysis as stemming from either supply or demand shocks. The results of this analysis show that neither supply nor demand shocks emerge as the primary driver of relative price changes. Moreover, the average returns associated with supply-based shocks are statistically indistinguishable from those associated with demand-based shocks. For this reason, our theoretical analysis remains largely agnostic regarding the micro-foundations of why relative prices change over time.

Following the framework proposed by Shapiro (2022), we assume that the price of each good or service i at each time t is determined by the interaction between an upward sloping linear supply curve and a downward sloping linear demand curve. Specifically, we assume that

$$q_{i,t} = \sigma_i p_{i,t} + \alpha_{i,t}, \tag{A.8}$$

$$p_{i,t} = -\delta_i q_{i,t} + \beta_{i,t}. \tag{A.9}$$

Here, $q_{i,t}$ ($p_{i,t}$) is quantity (price) of good i at time t, σ_i (δ_i) is the slope of the supply (demand) curve, and $\alpha_{i,t}$ ($\beta_{i,t}$) is the intercept of the supply (demand) curve.

If we interpret shifts in $\alpha_{i,t}$ in equation (A.8) as representing supply shocks and shifts in $\beta_{i,t}$ in equation (A.9) as representing demand shocks, then we re-write these previous two equations and estimate these quantities through the following two time-series regressions

$$\epsilon^s_{i,t} \equiv \Delta\alpha_{i,t} = (q_{i,t} - \sigma_i p_{i,t}) - (q_{i,t-1} - \sigma_i p_{i,t-1}), \tag{A.10}$$

$$\epsilon^d_{i,t} \equiv \Delta\beta_{i,t} = (\delta_i q_{i,t} + p_{i,t}) - (\delta_i q_{i,t-1} + p_{i,t-1}), \tag{A.11}$$

where $\varepsilon^s_{i,t}$ ($\varepsilon^d_{i,t}$) represents a supply (demand) shock to good i at time t. Collecting the similar coefficients in equations (A.10) and (A.11) allows us to write this system of equations as the following structural VAR

$$\boldsymbol{A}^i \boldsymbol{z}_{i,t} = \sum_{j=1}^{N} \boldsymbol{A}^i_j \boldsymbol{z}_{i,t-j} + \boldsymbol{\varepsilon}_{i,t}, \tag{A.12}$$

where $\boldsymbol{z}_{i,t} = \begin{bmatrix} q_{i,t} \\ p_{i,t} \end{bmatrix}$, $\boldsymbol{A}^i = \begin{bmatrix} 1 & -\sigma_i \\ \delta_i & 1 \end{bmatrix}$, $\boldsymbol{\varepsilon}_{i,t} = \begin{bmatrix} \varepsilon^s_{i,t} \\ \varepsilon^d_{i,t} \end{bmatrix}$, and N is the number of lags used to estimate this system. Pre-multiplying equation (A.12) by $\boldsymbol{A}^i$ yields a system that we estimate to obtain the reduced-form residuals $\boldsymbol{\phi}_{i,t}$

$$\boldsymbol{z}_{i,t} = \left[\boldsymbol{A}^i\right]^{-1} \sum_{j=1}^{N} \boldsymbol{A}^i_j \boldsymbol{z}_{i,t-j} + \left[\boldsymbol{A}^i\right]^{-1} \boldsymbol{\varepsilon}_{i,t},$$

$$\boldsymbol{z}_{i,t} = \left[\boldsymbol{A}^i\right]^{-1} \sum_{j=1}^{N} \boldsymbol{A}^i_j \boldsymbol{z}_{i,t-j} + \boldsymbol{\phi}_{i,t}. \tag{A.13}$$

Equation (A.13) hows how $\boldsymbol{A}^i$ provides a mapping between the structural and reduced-form via

$$\boldsymbol{\varepsilon}_{i,t} = \boldsymbol{A}^i \boldsymbol{\phi}_{i,t}.$$

Finally, and with this mapping in hand, Jump and Kohler (2022) show that in the context of the workhorse three-equation New Keynesian model, the signs of the reduced-form residuals in equation (A.13) are informative about the signs of the structural shocks in equation (A.12). These sign restrictions are given by

$$\text{Demand shock } (+): \phi^p_{i,t} > 0, \phi^q_{i,t} > 0 \rightarrow \varepsilon^d_{i,t} > 0, \tag{A.14}$$

$$\text{Demand shock } (-): \phi^p_{i,t} < 0, \phi^q_{i,t} < 0 \rightarrow \varepsilon^d_{i,t} < 0, \tag{A.15}$$

$$\text{Supply shock } (+): \phi^p_{i,t} < 0, \phi^q_{i,t} > 0 \rightarrow \varepsilon^s_{i,t} > 0, \tag{A.16}$$

$$\text{Supply shock } (-): \phi^p_{i,t} > 0, \phi^q_{i,t} < 0 \rightarrow \varepsilon^s_{i,t} < 0. \tag{A.17}$$

The above equations state that when innovations to prices and quantities have the same sign, then a demand shock has a occurred. Likewise, when innovations to prices and quantities move in opposite directions, then good or service i has experienced a supply shock at time t.

To empirically implement this framework, we gather detailed data on the quantity (price) indexes of various goods from Table 2.4.3U (Table 2.4.4U) in the "Underlying Detail" section of the BEA's website. In collecting this data, we constrain our analysis to the same set of indexes outlined in Table A.1. With this monthly price and quantity data in hand for the period spanning

January 2000 through December 2022, we obtain the reduced-form residuals underlying equation (A.12) by estimating the following time-series regressions

$$q_{i,t} = \sum_{j=1}^{12} \gamma_j^{qq} q_{i,t-j} + \sum_{j=1}^{12} \gamma_j^{qp} p_{i,t-j} + \phi_{i,t}^{q}, \tag{A.18}$$

$$p_{i,t} = \sum_{j=1}^{12} \gamma_j^{pq} q_{i,t-j} + \sum_{j=1}^{12} \gamma_j^{pp} p_{i,t-j} + \phi_{i,t}^{p}. \tag{A.19}$$

Here, $q_{i,t}$ and $p_{i,t}$ are the log quantity and prices indexes of good i at time t, respectively.

Although equations (A.14) to (A.17) provide a means to interpret the reduced-form residuals from equations (A.18) and (A.19) as relating to either a fundamental supply or demand shock to good i at time t, these sign restrictions are subject to the concern that the estimated values of these reduced-form residuals may be close to zero. If either one of these two reduced-form residuals is close to zero, then the sign-based restrictions discussed above may incorrectly label the fundamental drivers of a shock. To minimize the possibility that we are misclassifying supply- and demand-driven price changes, we define the fundamental driver of the price change of good i at time t as "ambiguous" if the estimated value of either $\phi_{i,t}^{q}$ or $\phi_{i,t}^{p}$ is sufficiently close to zero. We follow Shapiro (2022) in defining what constitutes the classification of "ambiguous" by setting each reduced-form residual equal to zero if its estimated value is less than 0.05 standard deviations away from zero. This results in us classifying about 14 percent of price changes as "ambiguous."

Figure A.2 reports the results of this analysis and shows the number of indexes that experience price changes for supply-related, demand-related, or ambiguous reasons in each month from January 2000 to December 2022. The key takeaway from this figure is that both supply- and demand-related prices changes are prevalent in the data. While slightly more than half of the price changes in the typical month are driven by various supply-related reasons, the number of demand-driven price changes are not so rare for us to ascribe a supply- or production-related interpretation to our main empirical results. Nevertheless, this prompts us to examine whether the average returns of firms that experience a supply shock differ from those that experience a demand shock.

To this end, we conduct a conditional portfolio sort exercise in which we sort the subset of CPI indexes underlying Figure A.2 into three portfolios in each month t on the basis of whether the index experienced a supply-driven, demand-driven, or ambiguous price change. In computing these

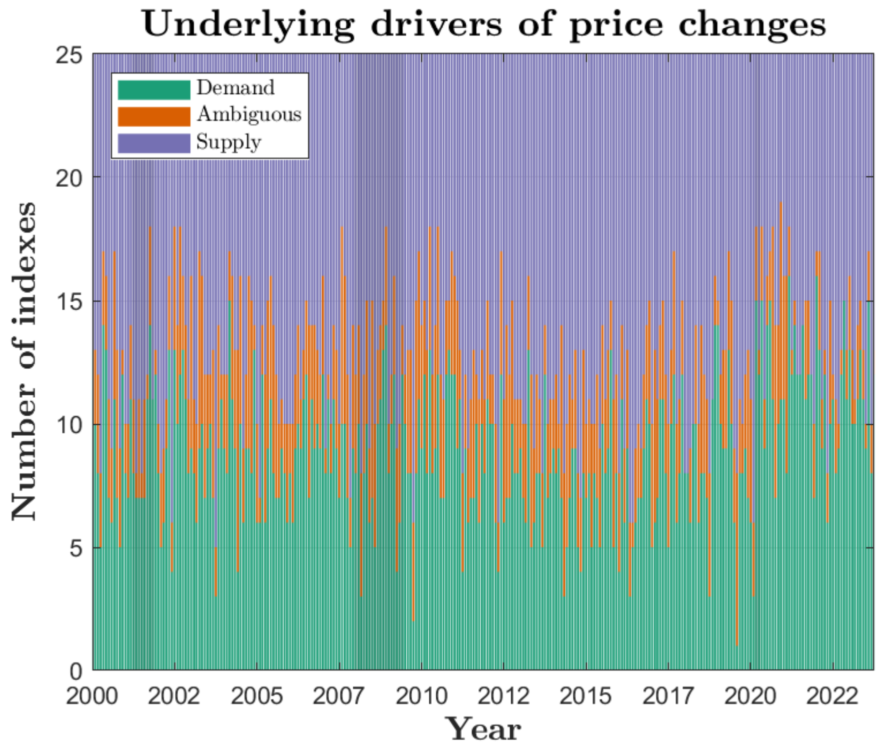


Figure A.2: Underlying drivers of price changes
The figure reports the results of attributing the price changes in the data to supply-related factors, demand-related factors, or ambiguous factors. The analysis draws on the methodology proposed by Shapiro (2022) and is implemented by following the details outlined in Section A.5. The underlying data required to implement this analysis is from the BEA and ranges from January 2000 through to December 2022.

index-level returns, we take the value-weighted average across all stocks assigned to a given index. Each portfolio-level return is then the equal-weighted average return across all the indexes assigned to the given portfolio. Each portfolio is held for one month, at which point in time all portfolios are rebalanced. This process results in a time-series of returns for each portfolio that ranges from February 2000 (as the first portfolio is formed at the end of January 2000) through to December 2022. The results of this analysis are reported in Table A.4.

Table A.4: Average returns associated with supply- and demand-driven shocks
The table reports the results of a conditional portfolio sort exercise in which the BLS price indexes reported in Table A.1 are sorted into one of three portfolios depending on whether the good or service in question experience a supply-related, demand-related, or ambiguous shock to its output price. Specifically, we estimate these shocks using the methodology discussed in Section A.5 and then, in each month t between January 2000 through to November 2022, we sort indexes into portfolios based on the type of shock that index experiences in a given month. The returns within each index are value weighted, while the returns of each portfolio are constructed as an equal-weighted average return across the indexes assigned to each portfolio. Each portfolio is held for one month, at which point in time all portfolios are rebalanced. This procedure produces a time series of portfolio returns that ranges from February 2000 through to December 2022. Finally, t-statistics, reported in parentheses, are computed using Newey and West (1987) standard errors.

Demand-driven (D)	Ambiguous	Supply-driven (S)	$S - D$
0.90	0.90	1.09	0.19
(2.68)	(2.76)	(3.42)	(1.18)

The results in Table A.4 show that while the average returns of firms that experience a supply-based shock to their output prices are 0.19% per month higher than the returns of firms that experience demand-based shocks, this difference is statistically indistinguishable from zero (t-statistic of 1.18).

A.6 Additional tables and figures

Table A.5: Correlation matrix
The table reports the monthly time-series correlation between relative price dispersion and key financial and macroeconomic indicators. Here, we compute relative price changes (ΔRP) by first setting τ in equation (1) equal to 12 and then calculating the inter-quartile range across all available subcomponents of CPI at time t. The monthly annualized growth rate of the industry production index in each month (IP) is obtained by computing the logarithmic change in the industrial production index between months t and $t-12$. The annualized rates of core and energy inflation, π^{Core} and π^{Energy} are computed in a similar fashion. The five year break-even inflation rate, denoted by π^{BEI}, is from FRED. Monthly excess stock returns (MKTRF) are obtained from the data library of Ken French and the level of macroeconomic uncertainty (UNC) is obtained from Sydney Ludvigson's data library. The sample period ranges from January 2000 through December 2022 for all correlations except those related to the break-even inflation rate. Due to data availability, the sample period for all correlations related to the break-even inflation rate range from February 2003 to December 2022.

	ΔRP	IP	MKTRF	π^{Core}	π^{Energy}	π^{BEI}	UNC
ΔRP	1.000	-0.199	-0.096	0.576	0.129	0.130	0.517
IP		1.000	-0.054	0.196	0.644	0.637	-0.579
MKTRF			1.000	-0.158	-0.132	0.022	-0.086
π^{Core}				1.000	0.393	0.478	0.239
π^{Energy}					1.000	0.716	-0.094
π^{BEI}						1.000	-0.269
UNC							1.000

Table A.6: Transition matrix between relative price sorted portfolios
The table shows the probability that a industry sorted into portfolio $i \in \{\text{Low, Medium, High}\}$ in month t, where i is the row index, is sorted into portfolio $j \in \{\text{Low, Medium, High}\}$ in month $t+1$, where j is the column index. Indexes are sorted into portfolios at the end of each month following the portfolio formation procedure described in Section 2.1. The sample period ranges from December 1999 through December 2022.

Portfolio in	Portfolio in month $t+1$		
month t	Low	Medium	High
Low	0.594	0.399	0.004
Medium	0.050	0.893	0.053
High	0.007	0.415	0.575

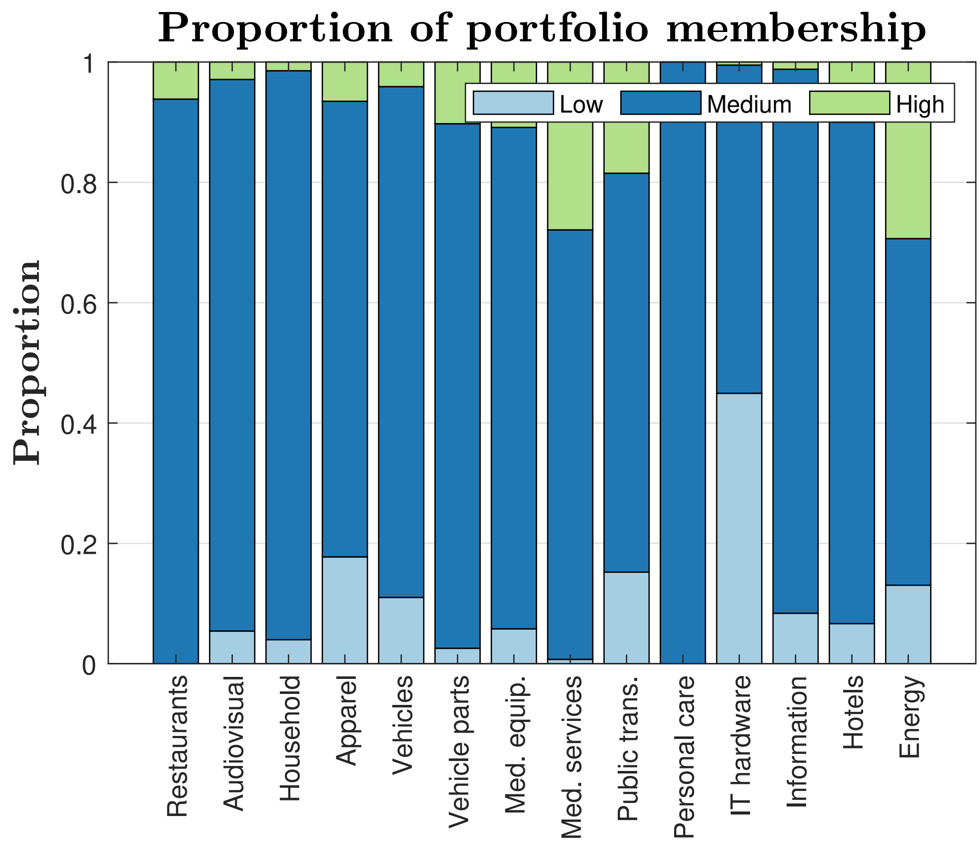


Figure A.3: Frequency of portfolio membership
The figure reports the proportion of months each industry is sorted into each of the low, medium, and high relative price sorted portfolios. In each portfolio formation month t from December 1999 to November 2022, the relative price portfolios are formed following the procedure described in Section 2.1. The sample period ranges from December 1999 through December 2022.

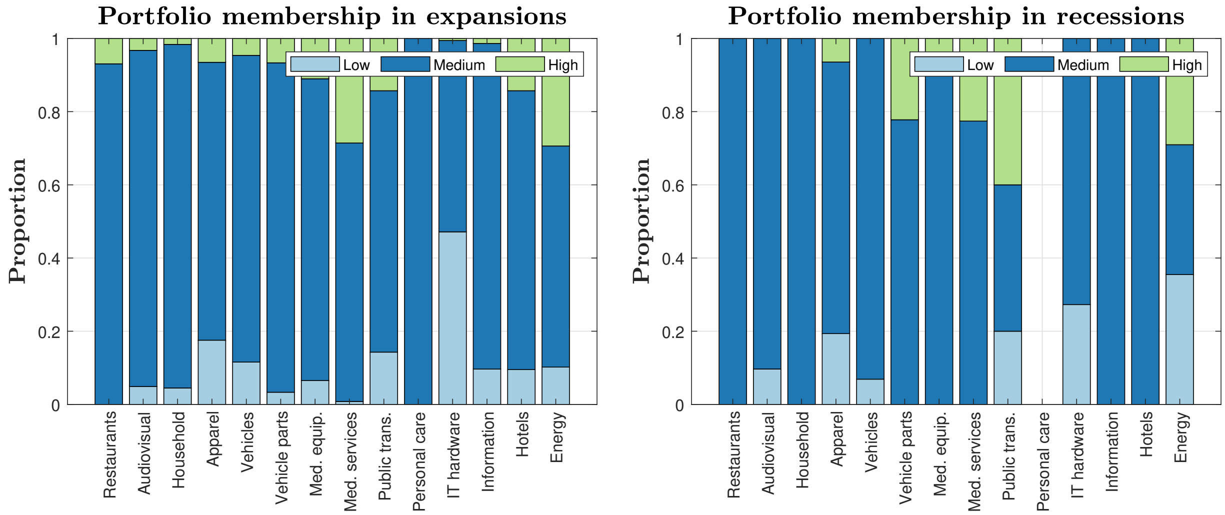


Figure A.4: Frequency of portfolio membership over the business cycle
The figure reports the proportion of months each industry is sorted into each of the low, medium, and high relative price sorted portfolios in both economic expansions (left panel) and economic recession (right panel). Here, define a portfolio formation month as belonging to a recession if the month falls within an NBER recession period. All remaining months are defined as belonging to an economic expansion. In each portfolio formation month t from December 1999 to November 2022, the relative price portfolios are formed following the procedure described in Section 2.1. The sample period ranges from December 1999 through December 2022.

Table A.7: Relative price premium with alternative portfolio breakpoints
The table reports the average monthly returns of portfolios sorted on the relative price changes (RP) from equation (1) and the spread between the returns of the low and high RP-sorted portfolios. In each portfolio formation month t from December 1999 through November 2022, the relative price portfolios are formed following the procedure described in Section 2.1 with two exceptions. First, Panel A reports the results of sorting industries into portfolios based on the 20^{th} and 80^{th} percentiles of the cross-sectional distribution of relative price changes in month $t-1$. Second, Panel B reports the results of sorting industries into portfolios based on the 30^{th} and 70^{th} percentiles of the cross-sectional distribution of relative price changes in month $t-1$. The table then reports the mean value-weighted portfolio returns associated with each alternative portfolio formation procedure (denoted by $\mathbb{E}[R]$) alongside the volatility of the monthly returns of these portfolios (denoted by $\sigma(R)$). The return data underlying these results ranges from January 2000 through December 2022. Finally, parentheses report Newey and West (1987) robust t-statistics.

	Panel A: 20/80 breakpoints		Panel B: 30/70 breakpoints	
	$E[R]$	$\sigma(R)$	$E[R]$	$\sigma(R)$
Low (L)	0.66	5.15	0.50	5.52
Medium	0.88	4.47	0.89	4.75
High (H)	1.20	4.60	0.99	4.59
Spread	0.54	4.19	0.49	3.47
(H-L)	(2.24)		(2.75)	

Table A.8: Relative price premium excluding food and energy

The table reports the average monthly returns of portfolios sorted on the relative price changes (RP) from equation (1) and the spread between the returns of the low and high RP-sorted portfolios. In each portfolio formation month t from December 1999 through November 2022, the relative price portfolios are formed following the procedure described in Section 2.1 with two exceptions. First, Panel A excludes all food-related industries from the portfolio formation procedure. Second, Panel B excludes all energy-related firms from the portfolio formation procedure. The table then reports the mean value-weighted portfolio returns associated with each alternative portfolio formation procedure (denoted by $\mathbb{E}[R]$) alongside the volatility of the monthly returns of these portfolios (denoted by $\sigma(R)$). The return data underlying these results ranges from January 2000 through December 2022. Finally, parentheses report Newey and West (1987) robust t-statistics.

	Panel A: Excluding food		Panel B: Excluding energy	
	$E[R]$	$\sigma(R)$	$E[R]$	$\sigma(R)$
Low (L)	0.36	6.25	0.46	6.03
Medium	0.83	4.62	0.86	3.97
High (H)	1.33	5.81	1.25	4.89
Spread	0.97	4.85	0.79	4.11
(H-L)	(3.71)		(3.09)	

Table A.9: Relative price premium with alternative standard errors and non-overlapping returns

The table reports the average monthly returns of portfolios sorted on the relative price changes (RP) from equation (1) and the spread between the returns of the low and high RP-sorted portfolios. In each portfolio formation month t from December 1999 through November 2022, the relative price portfolios are formed following the procedure described in Section 2.1 with two exceptions. First, since the baseline portfolio formation procedure results in a time series of monthly overlapping returns, Panel A reports t-statistics constructed using Hodrick (1992) standard errors in place of Newey and West (1987) standard errors. Second, Panel B reports the results obtained by using non-overlapping portfolio returns. In this case, the portfolio formed at the end of month t is held until the end of month $t + 1$, at which point in time all portfolios are rebalanced. Each panel reports the mean return (denoted by $\mathbb{E}[R]$) alongside the volatility of returns (denoted by $\sigma(R)$) associated with each portfolio. The return data underlying these results ranges from January 2000 through December 2022. Finally, the parentheses in Panel B reports the Newey and West (1987) robust t-statistic.

	Panel A: Hodrick (1992) s.e.		Panel B: Non-overlapping returns	
	$E[R]$	$\sigma(R)$	$E[R]$	$\sigma(R)$
Low (L)	0.26	6.07	0.63	6.14
Medium	0.84	4.69	0.88	4.41
High (H)	1.14	5.17	1.29	5.62
Spread	0.88	5.01	0.66	6.36
(H-L)	(3.27)		(1.71)	

Table A.10: Relative price premium including more granular and aggregate price indexes
The table reports the average monthly returns of portfolios sorted on the relative price changes (RP) from equation (1) and the spread between the returns of the low and high RP-sorted portfolios. In each portfolio formation month t from December 1999 through November 2022, the relative price portfolios are formed following the procedure described in Section 2.1 with two exceptions. First, while our benchmark portfolio formation procedure excludes any price index that is matched to fewer than 30 underlying firms, Panel A augments this approach to include more granular price indexes that are matched to five or more firms. Second, while our benchmark portfolio formation procedure excludes any aggregate price index that "overlaps" with its more granularly-defined subcomponents, Panel B also includes these aggregate indexes in our portfolios. The table then reports the mean value-weighted portfolio returns associated with each alternative portfolio formation procedure (denoted by $\mathbb{E}[R]$) alongside the volatility of the monthly returns of these portfolios (denoted by $\sigma(R)$). The return data underlying these results ranges from January 2000 through December 2022. Finally, parentheses report Newey and West (1987) robust t-statistics.

	Panel A: Inc. granular indexes		Panel B: Inc. aggregate indexes	
	$E[R]$	$\sigma(R)$	$E[R]$	$\sigma(R)$
Low (L)	0.39	6.04	0.53	5.18
Medium	0.90	4.13	0.85	4.08
High (H)	1.34	5.20	1.22	5.24
Spread	0.95	4.46	0.69	4.60
(H-L)	(3.36)		(2.53)	

Table A.11: Portfolio α's with industry momentum and BAB factor

This table reports the results of regressions of the relative price premium (i.e., the value-weighted returns of the portfolio that buys firms associated with high relative price changes and sells firms associated with low relative price changes) on common unconditional asset-pricing factors factors. Here, parameter estimates are obtained by regressing monthly excess returns on each set of monthly factors. MKTRF is the excess return of the market portfolio. SMB and HML are the size and value factors of the Fama and French (1993), while UMD is the momentum factor of Carhart (1997). Profit. and Invest. correspond to RMW and CMA factors (ROE and I/A factors) of the Fama and French (2015) five-factor model (Hou et al. (2021) q^t model). EG represents the expected growth factor from Hou et al. (2021) q^5 model. Finally, each column includes the industry momentum ("Ind. Mom.") spread documented by Moskowitz and Grinblatt (1999). Parentheses report Newey and West (1987) robust t-statistics. Returns span January 2000 to December 2021.

	CAPM	FF3F	FF4F	FF5F	FF6F	q^5
α	1.00	1.01	1.01	0.95	0.96	0.77
	(3.19)	(3.04)	(3.14)	(3.04)	(3.15)	(2.19)
MKTRF	-0.28	-0.27	-0.22	-0.25	-0.21	-0.19
	(-3.17)	(-3.24)	(-2.54)	(-3.08)	(-2.51)	(-2.16)
Size		-0.08	-0.12	-0.06	-0.09	0.03
		(-0.77)	(-1.07)	(-0.47)	(-0.68)	(0.24)
HML		0.27	0.33	0.22	0.30	
		(2.15)	(2.68)	(1.33)	(1.75)	
UMD			0.20		0.09	
			(1.66)		(0.29)	
Profit.				0.04	0.05	0.21
				(0.23)	(0.29)	(1.14)
Invest.				0.13	0.09	0.45
				(0.57)	(0.40)	(2.87)
EG						0.55
						(0.22)
IndMOM	0.10	0.12	0.05	0.12	0.05	0.09
	(1.59)	(2.25)	(0.83)	(2.22)	(0.83)	(1.49)
BAB	-0.02	-0.11	-0.17	-0.12	-0.18	-0.14
	(-0.16)	(-0.90)	(-1.51)	(-0.86)	(-1.49)	(-1.13)
$\bar{R}^2$	9.33	12.38	14.11	11.85	13.43	13.34

Table A.12: Relative price premium using real-time data
The table reports the average monthly returns of portfolios sorted on relative price changes (RP) from equation (1) and the spread between the returns of the low and high RP-sorted portfolios. In each portfolio formation month t from December 1999 to November 2022, the relative price portfolios are formed following the procedure described in Section 2.1. However, rather than using CPI data from FRED to measure the relative price changes associated with each index, we use real-time vintages of data from ALFRED. The table then reports the mean value-weighted portfolio returns associated with the relative price premium (denoted by $\mathbb{E}[R]$) alongside the volatility of the monthly returns of these portfolios (denoted by $\sigma(R)$). The return data underlying these results ranges from January 2000 to December 2022. Finally, parentheses report Newey and West (1987) robust t-statistics.

	$E[R]$	$\sigma(R)$
Low (L)	0.29	5.46
Medium	0.82	4.26
High (H)	1.06	5.10
Spread	0.77	4.10
(H-L)	(3.20)	

Table A.13: Relative price premium using non-conglomerate pure play firms
The table reports the average monthly returns of portfolios sorted on the relative price changes (RP) from equation (1) and the spread between the returns of the low and high RP-sorted portfolios. In each portfolio formation month t from December 1999 through November 2022, the relative price portfolios are formed following the procedure described in Section 2.1. However, any firm that is part of a conglomerate (as identified by following the procedure outlined by Hoberg and Phillips (2018)) is removed from analysis. The table then reports the mean value-weighted portfolio returns associated with the relative price premium (denoted by $\mathbb{E}[R]$) alongside the volatility of the monthly returns of these portfolios (denoted by $\sigma(R)$). The return data underlying these results ranges from January 2000 through December 2022. Finally, parentheses report Newey and West (1987) robust t-statistics.

	$E[R]$	$\sigma(R)$
Low (L)	0.14	6.51
Medium	0.98	4.63
High (H)	1.11	5.57
Spread	0.97	5.90
(H-L)	(2.96)	

Table A.14: Relative price premium with unconditional portfolio formation procedure
The table reports the average monthly returns of portfolios sorted on the relative price changes (RP) from equation (1) and the spread between the returns of the low and high RP-sorted portfolios. The relative price portfolios are formed following the procedure described in Section 2.1 with one exception. Rather than sorting industries into portfolios at the end of each portfolio formation month t from December 1999 through November 2022, we assign each industry to a single portfolio based on that industries average relative price change over the entire sample period. The table then reports the mean value-weighted portfolio returns associated with the relative price premium (denoted by $\mathbb{E}[R]$) alongside the volatility of the monthly returns of these portfolios (denoted by $\sigma(R)$). The return data underlying these results ranges from January 2000 through December 2022. Finally, parentheses report Newey and West (1987) robust t-statistics.

	$E[R]$	$\sigma(R)$
Low (L)	0.88	6.21
Medium	0.82	4.15
High (H)	0.83	4.00
Spread	-0.05	4.95
(H-L)	(-0.17)	

Table A.15: Relative price premium after excluding difficult to trade firms
The table reports the average monthly returns of portfolios sorted on the relative price changes (RP) from equation (1) and the spread between the returns of the low and high RP-sorted portfolios. In each portfolio formation month t from December 1999 through November 2022, the relative price portfolios are formed following the procedure described in Section 2.1 with one of three exceptions. First, Panel A excludes any firm that has a share price below $5 per share before forming portfolios. Second, Panel B removes any firm with a market capitalization below the cross-sectional median market capitalization rate on each portfolio formation date. Third, and finally, Panel C removes any firm with an idiosyncratic volatility above the cross-sectional median idiosyncratic volatility on each portfolio formation date. To ensure that there are sufficient firms underlying each industry after applying these filter, we require that there are five or more firms underlying each industry included in the portfolio sorts. The table then reports the mean value-weighted portfolio returns associated with the relative price premium (denoted by $\mathbb{E}[R]$) alongside the volatility of the monthly returns of these portfolios (denoted by $\sigma(R)$). The return data underlying these results ranges from January 2000 through December 2022. Finally, parentheses report Newey and West (1987) robust t-statistics.

	Panel A: Price $\geq$ \$5		Panel B: High ME		Panel C: Low IVOL	
	$E[R]$	$\sigma(R)$	$E[R]$	$\sigma(R)$	$E[R]$	$\sigma(R)$
Low (L)	0.37	6.02	0.40	6.05	0.52	5.86
Medium	0.89	4.09	0.90	4.10	0.88	3.97
High (H)	1.34	5.19	1.34	5.22	1.29	5.13
Spread	0.97	4.43	0.94	4.50	0.77	4.48
(H-L)	(3.39)		(3.31)		(2.84)	

Table A.16: Relative price premium within momentum-sorted portfolios
The table reports the average monthly returns of portfolios sorted on the relative price changes (RP) from equation (1) and the spread between the returns of the low and high RP-sorted portfolios, constructed using the groups of firms with either low or high firm-level momentum, constructed by following Carhart (1997). Specifically, in each portfolio formation month t from December 1999 to November 2022, the relative price portfolios are formed following the procedure described in Section 2.1. However, rather than using the firm-level stock returns of all firms underlying these indexes, we use only the group of firms with stock return momentum below (above) the cross-sectional median value of momentum in each month to construct the relative price premium among low (high) momentum firms. The table then reports the mean value-weighted portfolio returns associated with each alternative portfolio formation procedure (denoted by $\mathbb{E}[R]$) alongside the volatility of the monthly returns of these portfolios (denoted by $\sigma(R)$). The return data underlying these results ranges from January 2000 to December 2022. Finally, parentheses report Newey and West (1987) robust t-statistics.

	Panel A: Low MOM		Panel B: High MOM	
	$E[R]$	$\sigma(R)$	$E[R]$	$\sigma(R)$
Low (L)	0.20	8.14	0.55	5.86
Medium	1.01	5.61	0.87	4.09
High (H)	1.11	6.59	1.16	5.54
Spread	0.90	6.14	0.60	4.59
(H-L)	(2.36)		(2.37)	

Table A.17: Independence from inflation- and durability-related spreads after controlling for excess market returns

This table documents the independence of the relative price premium (i.e., the value-weighted returns of the portfolio that buys high RP stocks and sells low RP stocks) from a number of spreads related to the level of inflation and asset durability. In particular, we look at the extent to which the relative price premium is linearly related to the inflation spread of Boons et al. (2020), spreads based on firms' exposures to each of headline inflation (π^{Headline}), core inflation (π^{Core}), and energy inflation (π^{Energy}), motivated by Fang et al. (2022), and the asset durability spread of Gomes et al. (2009). Details on the construction of the inflation betas underlying each spread are provided in Section A.1 of the Online Appendix. We implement this analysis by projecting the returns of the relative price premium on the returns associated with each of the aforementioned spreads and the excess market return, and then record the resulting intercepts (alphas). Parenthesis report t-statistics computed using Newey and West (1987) standard errors. Finally, returns span January 2000 to December 2022.

	(1)	(2)	(3)	(4)	(5)
α	1.04	1.04	1.04	1.03	1.03
	(3.96)	(4.10)	(4.09)	(4.00)	(4.13)
MKTRF	-0.33	-0.30	-0.32	-0.30	-0.36
	(-2.68)	(-3.14)	(-3.48)	(-3.13)	(-3.96)
$\pi^{\text{Boons et al.}}$	0.03				
	(0.21)				
π^{Headline}		-0.04			
		(-0.60)			
π^{Core}			-0.03		
			(-0.56)		
π^{Energy}				-0.02	
				(-0.38)	
Durability					0.29
					(2.06)
$\bar{R}^2$	7.78	7.94	7.89	7.83	9.66

Table A.18: Relative price premium after removing low-weight industries

The table reports the average monthly returns of portfolios sorted on the relative price changes (RP) from equation (1) and the spread between the returns of the low and high RP-sorted portfolios. The relative price portfolios are formed following the procedure described in Section 2.1 with one exception. Specifically, any industry that has a below-median weight in the CPI in the portfolio formation month is removed from the analysis. The table then reports the mean value-weighted portfolio returns associated with the relative price premium (denoted by $\mathbb{E}[R]$) alongside the volatility of the monthly returns of these portfolios (denoted by $\sigma(R)$). The return data underlying these results ranges from January 2000 through December 2022. Finally, parentheses report Newey and West (1987) robust t-statistics.

	$E[R]$	$\sigma(R)$
Low (L)	0.25	6.35
Medium	0.87	4.52
High (H)	1.31	4.91
Spread	1.06	5.68
(H-L)	(3.64)	

Table A.19: Relative price premium with prices changes defined over alternative horizons
The table reports the average monthly returns of portfolios sorted on the relative price changes (RP) from equation (1) and the spread between the returns of the low and high RP-sorted portfolios. In each portfolio formation month t from December 1999 through November 2022, the relative price portfolios are formed following the procedure described in Section 2.1 with two exceptions. First, while our benchmark portfolio formation procedure defines relative price changes in equation (1) over the past three months (i.e., using $\tau = 3$), here we use either semi-annual (i.e., $\tau = 6$) or annual (i.e., $\tau = 12$) months. The results from the portfolio sorts based on semi-annual and annual changes are reported in Panel A and Panel B, respectively. Second, given the difference in the horizons over which the relative price changes are defined, we do not employ overlapping returns. The mean value-weighted portfolio returns associated with each alternative portfolio formation procedure (denoted by $\mathbb{E}[R]$) alongside the volatility of the monthly returns of these portfolios (denoted by $\sigma(R)$). The return data underlying these results ranges from January 2000 through December 2022. Finally, parentheses report Newey and West (1987) robust t-statistics.

	Panel A: Semi-annual ($\tau = 6$)		Panel B: Annual ($\tau = 12$)	
	$E[R]$	$\sigma(R)$	$E[R]$	$\sigma(R)$
Low (L)	0.54	6.33	0.64	6.50
Medium	0.80	4.72	0.77	4.62
High (H)	1.17	5.84	1.37	6.23
Spread	0.63	6.12	0.73	6.02
(H-L)	(1.71)		(2.05)	

Table A.20: Pricing the returns of alternative test assets

The table reports statistics related to the ability of innovations to relative price dispersion to price the returns of a variety of alternative test assets. Specifically, we posit that the SDF is given by equation (7) and is driven by the market's excess return ($MKTRF_t$) and innovations to relative price dispersion (ΔRP_t). We compute the innovations to relative prices using the logarithmic first difference of changes in the inter-quartile range of relative prices changes, obtained from equation (1). The table then reports the market prices of risk associated with $MKTRF_t$ and ΔRP_t when the test assets are (1) 25 portfolios sorted on size and book-to-market ratios, (2) six portfolios sorted on size and investment rates, (3) six portfolios sorted on size and profitability, (4) 37 portfolios that combine the previous three sets of test assets, and (5) 54 portfolios that add the returns of the 17 Fama-French industry portfolios to the previous set of test assets. All test asset returns are obtain from Ken French's data library. The sample underlying this table spans from January 2000 to December 2022 and parentheses report Newey and West (1987) robust t-statistics.

	(1)		(2)		(3)		(4)		(5)	
	25 SZ-BM		6 SZ-IK		6 SZ-OP		37 SZ-BM, SZ-OK, SZ-OP		54 SZ-BM, SZ-IK SZ-OP, Industry	
λ_{MKTRF}	0.24	0.21	0.15	0.19	0.21	0.21	0.29	0.22	0.36	0.22
	(3.91)	(3.66)	(2.13)	(2.44)	(2.83)	(2.46)	(5.24)	(4.84)	(8.57)	(6.25)
$\lambda_{\Delta RP}$		-0.65		-0.61		-1.05		-0.61		-0.67
		(-4.98)		(-1.99)		(-2.15)		(-6.12)		(-9.19)
MAE	0.49	0.32	0.18	0.18	0.44	0.24	0.79	0.47	1.24	0.53

Table A.21: Relative price premium excluding economic recessions
The table reports the average monthly returns of portfolios sorted on the relative price changes (RP) from equation (1) and the spread between the returns of the low and high RP-sorted portfolios. In each portfolio formation month t from December 1999 through November 2022, the relative price portfolios are formed following the procedure described in Section 2.1. In Panel A, we report the relative price premium excluding the COVID-19 crisis from January 2020 to December 2022. In Panel B, we exclude the Global Financial Crisis (GFC) ranging from January 2008 to June 2009. Finally, in Panel C, we report the relative price premium after exlcuding the COVID-19 crisis, the GFC, and the early 2000s recession from March to November 2001. The return data underlying these results ranges from January 2000 through December 2022. The parentheses report Newey and West (1987) robust t-statistics.

	Panel A: COVID-19		Panel B: GFC		Panel C: All recessions	
	$E[R]$	$\sigma(R)$	$E[R]$	$\sigma(R)$	$E[R]$	$\sigma(R)$
Low (L)	0.42	5.71	0.54	5.64	0.86	4.91
Medium	0.83	4.46	0.98	4.27	1.05	3.71
High (H)	1.16	5.10	1.37	4.77	1.51	4.49
Spread (H-L)	0.74	4.89	0.83	5.21	0.65	4.63
(H-L)	(2.80)		(2.79)		(2.44)	

Table A.22: Summary statistics for the relative prices of each index of CPI. The table reports mean, standard deviation (SD), and autocorrelation coefficients of the relative price changes, defined in equation (1) where we set $\tau = 3$. AR(1), AR(3), and AR(12) indicate coefficients of the autoregressive model of order 1, 3, and 12, respectively. We combine these 43 indexes into eight main categories listed in the first eight rows. We use data compiled by the U.S. BLS. Data spans January 2000 to December 2022.

	BLS ID	Name	Mean	SD	AR(1)	AR(3)	AR(12)
1	CPIFABSL	Food and beverages	0.07	0.76	0.78	0.06	-0.19
2	CUSR0000SAF11	Food at home	0.02	0.98	0.78	0.11	-0.18
3	CPIHOSNS	Housing	0.06	0.57	0.76	0.04	-0.01
4	CUSR0000SAE2	Communication	-0.88	1.01	0.77	0.23	0.01
5	CPITRNSL	Transportation	0.01	2.81	0.77	0.02	-0.11
6	CPIRECSL	Recreation	-0.33	0.68	0.74	0.01	-0.10
7	CPIMEDSL	Medical care	0.22	0.80	0.79	0.18	-0.02
8	CPIOGSSL	Other	0.11	0.84	0.69	0.13	0.01
9	CPIAPPSL	Apparel	-0.65	0.97	0.70	0.04	0.03
10	CUSR0000SAE21	Information	-0.82	1.04	0.81	0.30	-0.05
11	CUSR0000SAF111	Bakery	0.05	1.09	0.79	0.30	-0.15
12	CUSR0000SAF112	Meat	0.21	1.63	0.76	0.08	-0.17
13	CUSR0000SAF113	Fruits	-0.03	1.84	0.62	-0.37	-0.24
14	CUSR0000SAF114	Beverages	-0.14	1.16	0.68	0.00	-0.21
15	CUSR0000SAF116	Alcohol	-0.09	0.75	0.76	0.04	-0.18
16	CUSR0000SAG1	Personal care	-0.10	0.69	0.74	-0.08	-0.13
17	CUSR0000SAH2	Fuels and Utilities	0.31	1.79	0.80	0.28	-0.19
18	CUSR0000SAH3	Household	-0.47	0.77	0.78	0.15	-0.10
19	CUSR0000SAM1	Medical equipment	-0.06	0.95	0.77	0.20	0.10
20	CUSR0000SAM2	Medical services	0.30	0.80	0.79	0.17	-0.05
21	CUSR0000SAT1	Private transportation	0.04	2.92	0.76	0.02	-0.11
22	CUSR0000SEAE	Footwear	-0.46	1.21	0.64	-0.18	-0.17
23	CUSR0000SEEE	IT and hardware	-1.49	1.57	0.85	0.38	0.10
24	CUSR0000SEFJ	Dairy	-0.06	1.81	0.79	0.16	-0.17
25	CUSR0000SEFP01	Coffee	0.01	1.99	0.75	0.27	-0.24
26	CUSR0000SEFR	Sweets	-0.01	1.26	0.65	-0.00	-0.00
27	CUSR0000SEFS	Fats	0.18	1.65	0.78	0.42	-0.11
28	CUSR0000SEFT	Other foods	-0.08	1.06	0.75	0.15	-0.24
29	CUSR0000SEFV	Restaurants	0.16	0.69	0.79	0.09	-0.14
30	CUSR0000SEGA	Tobacco	0.80	2.30	0.61	0.14	0.09
31	CUSR0000SEGD03	Laundry	0.14	0.74	0.69	-0.05	-0.17
32	CUSR0000SEHB	Hotels	-0.10	2.55	0.61	-0.08	-0.17
33	CUSR0000SERA	Video and Audio	-0.49	0.84	0.79	0.21	0.01
34	CUSR0000SERE01	Toys	-2.03	1.22	0.65	-0.04	-0.10
35	CUSR0000SERE03	Music	-0.41	1.46	0.63	-0.20	0.05
36	CUSR0000SERF01	Clubs	-0.21	1.39	0.63	-0.27	-0.03
37	CUSR0000SETA	Vehicles	-0.36	1.46	0.79	0.05	0.04
38	CUSR0000SETB	Motor fuel	0.56	11.42	0.74	-0.06	-0.08
39	CUSR0000SETC	Vehicle parts	0.01	0.96	0.78	0.27	0.09
40	CUSR0000SETD	Vehicle maintenance	0.18	0.83	0.76	0.13	-0.09
41	CUSR0000SETG	Public transportation	-0.27	3.56	0.74	-0.10	-0.00
42	CUSR0000SETG01	Airfares	-0.37	5.70	0.76	-0.11	0.00
43	CUSR0000SS61031	Pet foods	0.03	1.36	0.83	0.37	-0.07