The Leading Premium

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Abstract

In this paper, we compute conditional measures of lead-lag relationships between GDP growth and industry-level cash-flow growth in the US. Our results show that firms in leading industries pay an average annualized return 4% higher than that of firms in lagging industries. Using both time series and cross sectional tests, we estimate an annual timing premium ranging from 1.5% to 2%. This finding can be rationalized in a model in which (a) agents price growth news shocks, and (b) leading industries provide valuable resolution of uncertainty about the growth prospects of lagging industries.

JEL classification: G10; E32; E44.

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1 Introduction

Different macroeconomic aggregates go through economic cycles with different timings (see, among others, Stock and Watson 1989, 2002; and Estrella and Mishkin 1998). Variables that respond promptly to exogenous shocks are denoted as "leading," whereas variables that adjust with delay are called "lagging."[1] Thus far, the empirical macroeconomic literature has focused mainly on leads and lags of aggregate indicators. Little is yet known about leads and lags across firms operating in different segments of the economy.

In this paper, we document the existence of a significant lead-lag structure in fundamental cash flows across industries. This structure is relevant to the explanation of the cross section of stock returns, as leading industries pay a higher average stock return than lagging industries, in the order of about 4% per year. After controlling for heterogenous exposure to a large number of aggregate risk factors, we obtain an estimate of the pure timing premium, i.e., the premium on advance information (Ai and Bansal, 2018), ranging from 1.5% to 2% per year.[2]

Specifically, we construct a risk factor by considering a zero-dollar investment strategy long in a portfolio of leading industries and short in a portfolio of lagging industries. We denote the returns of this portfolio as the LL factor. Formal tests show that LL is a relevant factor both in the time series and in many cross sections of equity returns, including that of industry portfolio returns (in contrast to the factors considered by, e.g., Fama and French 1997). This result holds after controlling for many other aggregate factors (see, e.g., Gomes et al. 2009) and suggests that leads and lags in the diffusion of fundamental shocks across industries are an important dimension of equity pricing. Equivalently, the information timing premium appears sizeable.

More broadly, our results provide additional and independent empirical evidence in favor

[1]For example, both bond yields and the stock market index tend to be leading indicators with respect to domestic output, as they forecast future recessions and booms. Unemployment, in contrast, is a lagging indicator.

[2]Consider a risk factor F_t, a leading firm (or sector) with cash flow growth $\Delta d_t^{Lead} = \mu + \lambda^{Lead} F_t$, and a lagging firm (or industry) with cash flow growth $\Delta d_t^{Lag} = \mu + \lambda^{Lag} F_{t-LL}$. The leading premium is a convolution of heterogeneous timing of exposure, LL, and heterogenous exposure $\lambda^{Lag} \neq \lambda^{Lead}$. We control for heterogenous exposure by considering several cycle-related risk factors and refer to the residual difference in the cost of equity of the two stocks, or sectors, as the (pure) timing premium.

of the relevance of advance information in the spirit of Ai and Bansal (2018). Consistent with this observation, we show that our findings are an anomaly in a model with time-additive preferences, whereas a model with news shocks and preferences for early resolution of uncertainty explains our cross-sectional results. This is because leading industries provide valuable anticipated resolution of uncertainty for industries that go through aggregate economic fluctuations with delay. As a result, lagging firms bear less conditional cash-flow uncertainty and, by no arbitrage, ceteris paribus have a higher price (or, equivalently, a lower yield). Leading firms, in contrast, play the role of early indicators like canaries in a coal mine and pay a higher equity yield.

More specifically, we compute rolling-window correlations between US output growth and leads and lags of operating income growth at an industry level. Data are quarterly and span the period 1972–2012. We consider 17,000 firms, which we aggregate to industries using the industry classification scheme obtained from Kenneth French's website.[3] In each quarter, we compute cross-correlagrams and aggregate leads and lags in three different ways as described below in Section 2. We then assign the corresponding lead/lag indicator to the industry of interest. Note that this approach uses only past data to compute the cross-correlograms, and hence it can be used to construct an implementable investment strategy in real-time.

This procedure gives us a panel of quarterly leading-lagging indicators spanning 41 years of data. In each sample period, we find sizable heterogeneity in these indicators across our industries. Focusing on individual industries, we also observe considerable fluctuations in the time series of their lead and lag indicators, i.e., an industry may be leading in a specific period, but lagging in another. As an example, the firms leading during an IT boom do not necessarily lead during a financial crisis. We formalize this idea in a multisector economy in which cash flows are affected by infrequently arriving shocks that slowly diffuse across all sectors and turn into aggregate cash flow growth shocks.

We then sort our firms according to their industry-level lead-lag indicator and form three portfolios, which are dynamically updated at a quarterly frequency. In each quarter, we

[3]See, for example, `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_30_ind_port.html`.

make sure that the extreme portfolios have a market capitalization share of at least 15%, so that our results are not driven by a subset of small and illiquid firms. According to this standard procedure, we find a monotonic positive relation between the average returns and the leading indicators of our portfolios. Our LL factor has an annualized average return of 4%, which remains sizeable and significant in the time-series after controlling for a large number of aggregate factors.

Furthermore, we show that our findings are statistically significant after double-sorting on LL exposure and either the book-to-market ratio or size, implying that the LL premium is a broad phenomenon in the cross section. We also show that our risk factor is not subsumed by other cyclical factors such as investment minus consumption (Kogan and Papanikolaou 2014), durability (Gomes et al. 2009), industry-momentum (Moskowitz and Grinblatt 1999), industry betting-against-beta (Asness et al. 2014), the five factors suggested by Fama and French 2015, the q-Factors (Hou et al. 2015a, b), and momentum (Carhart 1997).

A simple no arbitrage argument shows that our leading premium should be related to the forward equity yield on leading industry dividends (Binsbergen et al. 2013). This result is important because it suggests that models that produce a substantial positive spread between bond and zero-coupon equity yields may rationalize the portion of the leading premium driven by the timing premium. Since our empirical evidence shows that lagging firms tend to have smoother long-run dividend growth, we choose a setting sensitive to growth news shocks (Bansal and Yaron 2004).

We acknowledge that lagging firms can learn from the fundamentals of leading firms and adjust their investment decisions to endogenously alter their pay outs (see, among others, Albuquerque and Miao 2014). For the sake of tractability, however, we abstract away from investment decisions and consider the endowment economy of Bansal et al. (2005), in which stocks are allowed to have heterogenous exposure to long-run shocks. Consistent with our empirical evidence, we allow lagging stocks to be less exposed to growth news shocks. We use this model to price a cross section of cash flows that differ from each other also in their lead-lag structure, with the goal of quantifying how much of both our timing and leading premiums we can explain.

The relevance of this step is twofold. On the one hand, we identify the lead-lag structure of cash flows and better characterize the composition of the representative agent's information set, that is, we identify how much advance information the agent can obtain from the leading cash flows. On the other hand, this procedure shows that a substantial part of our measured timing and leading premiums may be explained by our equilibrium model.

We conclude our analysis with a counterfactual experiment designed to quantify the welfare value of the advance information provided by the leading industries. Specifically, we look at an economy calibrated as in our benchmark case, where we simply remove future long-run consumption growth news from the information set of the agent. Put differently, we retain the same amount of consumption long-run risk, but we pretend that there is no leading portfolio providing advance information about it. We find that the welfare benefits of the information stemming from our cross section of industries are worth 6% of life-time consumption. In order to correctly interpret this result, we run the Lucas (1987) experiment in our economy and find that the welfare benefits of removing all uncertainty are in the order of 65%.[4] Therefore, the advance information that we identify in the cross section of industries represents less than 10% of the maximum attainable welfare benefits.

Epstein et al. (2014) point out that in the Bansal and Yaron (2004) model, the Lucas welfare benefits originate mainly from full resolution of uncertainty, not from the removal of deterministic fluctuations. Our computations show that early resolution of uncertainty in the cross section of industries is simultaneously valuable but limited, as it carries a strong market price of risk but reveals future long-run consumption dynamics over a relatively short horizon.

Related literature. As mentioned above, prior papers have already documented that heterogeneous exposure to contemporaneous news shocks can explain many cross sections of equity returns (see, among others, Bansal et al. 2005). We differ from prior studies by

[4]This figure is much smaller than that in Ai (2007) and Croce (2013), as our consumption process is calibrated according to post-1972 data, i.e., its volatility is moderate.

showing that *heterogeneous timing* of exposure to news shocks explains a substantial share of the leading premium.

Kadan and Manela (2016) estimate the value of information using options. We empirically quantify the relevance of heterogeneity in the timing of exposure of cash flows to aggregate shocks for the cross section of equity returns. Our results are significant beyond announcement events (Patton and Verado 2012, Savor and Wilson 2013, 2016).

Koijen et al. (2017) show that the Cochrane and Piazzesi (2005) factor is a strong predictor of economic activity, with a lead of up to 10 quarters relative to GDP growth. They provide evidence suggesting that book-to-market-sorted stocks contain information about future growth. Similarly to them, we show that the price-dividend ratio of leading firms forecasts economic activity, even after controlling for other common predictors.

Hong et al. (2007) investigate whether high-frequency industry *returns* can forecast excess returns on the CRSP market index. They find evidence of predictability, but only on very short horizons of one or two months. In contrast to previous studies, our empirical investigation is based on *cash-flow fundamentals* and focuses on longer time horizons. As a result, we are silent about the speed at which prices fully embody available information (Hou 2007, Cohen and Frazzini 2008). In our model, our endogenous cross section of *returns* features no lead-lag structure, that is, all returns move simultaneously, but with different endogenous sensitivities. On the other side, our attention on leads and lags across industry-level cash flows is broad and does not hinge on specific network links, like for example customer-to-supplier (Cohen and Frazzini 2008) or intermediate-to-final-producer (Gofman et al. 2017).

By no-arbitrage, the portion of the leading premium driven by the timing premium depends on the spread between the equity and the risk-free bond yield curve. Richer settings like those suggested by Lettau and Wachter (2007, 2011), and Belo et al. (2014) are consistent with the empirical evidence in Binsbergen et al. (2012), Binsbergen et al. (2013), and Binsbergen and Koijen (2017), but they would produce similar insights about the nature of the leading premium.

In the next section we provide intuition on our way to think of leads and lags across sectors. We present the setup and results of our empirical analysis in section 3. In Section 4 we describe our model. Section 5 concludes.

2 Measuring Leads and Lags

In this section, we discuss the measures that we adopt to identify leading and lagging industries. Since these measures are quite common in the macroeconomic literature, the readers familiar with cross-correlograms may want to go directly to the next section.

Consider the cash flow growth of industry i, ΔCF^i, and allow it to have a possibly time-varying lead-lag relation with output growth, ΔGDP. One way to identify the lead-lag link between aggregate output and the cash flow of this industry is to compute the following cross-correlogram over J periods

$$[\rho^i_{t,-J} \cdots \rho^i_{t,0} \cdots \rho^i_{t,+J}]$$

where

$$\rho^i_{t,j} = corr_{\{t-T \to t\}}(\Delta GDP_t, \Delta CF^i_{t-j})$$

is computed on a rolling window with $T > J$ observations. Since the cross-correlogram is of dimension $1 + 2J$, we use the following three ways to collapse it to a scalar, so that stocks can be easily sorted on it.

Maximum cross-correlation. Our first way to define our lead/lag indicator (LL) is

$$LL^i_t = \underset{-J \leq j \leq J}{\arg\max} |\rho^i_{t,j}|,$$

i.e., the lead or lag for which the cross-correlation between cash flow and GDP growth peaks in absolute value. As an example, assume that (i) ΔGDP_t follows an $AR(1)$ with persistence $0 < \rho < 1$, and (ii) $\Delta CF^i_{t-5} = -\Delta GDP_t$, so that GDP lags by a fixed delay and with opposite sign. In this case, $\rho^i_{t,j} = -\rho^{|j-5|}$ and $LL^i_t = +5$, that is, our indicator detects that the cash flow is leading aggregate output by 5 periods. This measure is consistent with the lead/lag assumptions in our simple asset pricing model in section 4.

Industry-level weighted average of leads and lags. When cash-flows and GDP do not follow AR(1) processes, the previous measure may not be appropriate as it may disregard information contained in the the whole cross-correlogram. One way to resolve this problem is to have an indicator that takes into account all possible leads and lags and gives more weight to the ones for which the cross-correlation is stronger in absolute value:

$$LL_t^i = \sum_{j=-J}^{J} \frac{|\rho_{t,j}^i|}{\sum_{j=-J}^{J} |\rho_{t,j}^i|} \cdot j.$$

Cross-industry weighted index of leads and lags. Another possible concern about the maximum correlation approach is that it does not adjust by the different predictive power that different industries may have. As an extreme example, one industry may lead GDP by four periods with a cross-correlation of 0.90 and be a much better predictor of GDP than an industry leading by four periods with a cross-correlation of 0.40. In order to address this concern, we also compute

$$LL_t^i = \sum_{j=-J}^{J} \frac{|\rho_{t,j}^i|}{\sum_{k=1}^{N} |\rho_{t,j}^k|} \cdot j,$$

where the weight assigned to lead/lag j of industry i depends on the cross-correlation of all of the other industries for the same lead/lag.

2.1 Intuition in a Simple Diffusion Model

Before proceeding with our empirical investigation, we introduce a simple diffusion model to provide intuition about our our way to identify conditionally leading and lagging industries. This model is stylized in many dimensions and is not meant to perfectly describe the data. Rather, our goal is to show that our cross-correlations have the potential to identify leading and lagging sectors when shocks diffuse across sectors connected in a network.

Consider an economy with $i = 1, ..., N \geq 3$ industries. In each industry, the cash flow growth rate is subject to both economy-wide short-run shocks, $\epsilon_{c,t} \sim N(0, \sigma_{sr})$, and a persistent industry-specific growth component:

$$S_t^i = \rho S_{t-1}^i + \epsilon_{x,t}^i.$$

We assume that sectoral growth news shocks are *i.i.d.* and arrive infrequently with probability q:

$$\epsilon_{x,t}^i = \begin{cases} J & q/2 \\ -J & q/2 \\ 0 & (1-q), \end{cases}$$

where J is the magnitude of the shocks, which, when not equal to zero, can be positive or negative with the same likelihood.

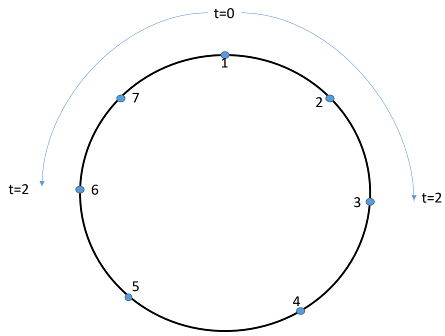
For the sake of symmetry, we let N be an odd integer and locate sectors on a circle in a clockwise order by means of the following index for locations:

$$f(i,j) = \begin{cases} i+j & 1 \leq i+j \leq N \\ i+j-N & i+j > N \\ N+(i+j) & i+j \leq 0. \end{cases}$$

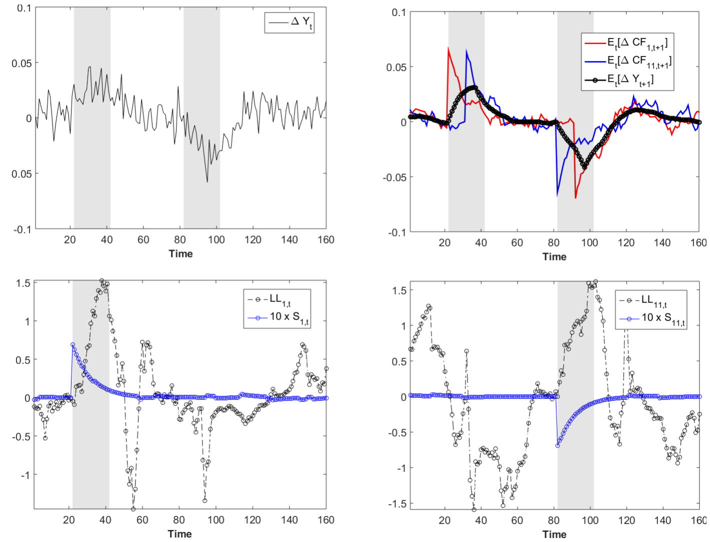
Consistent the simple example depicted in Figure 1(a), $f(i,j)$ is the index of a sector which is j units of distance (positive or negative) away from sector i. The sole purpose of the structure for $f(i,j)$ shown above is to make sure that the circle is actually closed, i.e., that sector N is to the immediate left of sector 1. We assume that a shock to sector i propagates symmetrically to the sectors located to both the right and the left of sector i with a certain delay. This means that it takes j periods for a shock originated in either location $f(i,-j)$ or $f(i,j)$ to reach sector i.

Given this notation, we specify the growth rate of the cash-flow of firm i as follows:

$$\Delta d_t^i := \log(D_t^i / D_{t-1}^i) = \mu + \epsilon_t^c + S_t^i + \sum_{j=1}^{(N-1)/2} \left(S_{t-j}^{f(i,-j)} + S_{t-j}^{f(i,j)} \right),$$



(a) Diffusion Example



(b) Simulation from Diffusion Model

Fig. 1: A Simple Diffusion Model

This figure depicts a quarterly simulation from the diffusion model described in Section 2.1. The lead-lag (LL) indicator indicator is computed in two steps. First, for each sector, in each quarter we compute the ±5-quarter cross-correlation between industry-level output growth and the domestic output growth using 40-quarter rolling windows ($\rho^i_{t,t-l}$, $l = -5, ..., 5$). Second, we compute the following weighted average of the leads and lags using the absolute value of the cross-correlations:

$$\sum_{j=-5}^{+5} j \cdot \frac{|\rho^i_{t,t+j}|}{\sum_{j=-5}^{+5} |\rho^i_{t,t+j}|}.$$

A positive (negative) LL indicator denotes an industry whose output growth leads (lags) GDP growth. Grey bars denote periods following a substantial shock to either sector 1 or 11.

and define aggregate GDP as:

$$Y_t = \sum_{i=1}^{N} D^i_t.$$

We choose our parameters in order to replicate key properties of US GDP. Specifically, the quarterly drift μ is set to 0.50% to have a 2% annual growth. We choose $\rho = .90$ as in our equilibrium model. To be consistent with our baseline cross section of industries, we choose $N = 31$. We set $q = 5\%$ so only a minority of our industries receive long-run shocks in a given period and lead future GDP expected growth. The parameters σ_{sr} and J are jointly chosen to match an annualized volatility of GDP growth of 2.3% and an autocorrelation of 0.21.

We show a representative quarterly simulation of this model in Figure 1(b). We focus on both aggregate output and the cash flows of industry 1 and 11, that is, industries that are affected by long-run growth shocks with a time difference of 10 periods.

For illustrative purposes only, we assume that industry 1 is affected by a pronounced positive shock at time 20 and that industry 11 is affected by a pronounced negative shock at time 80. This allows us to know exactly which industry will leading, even if we are simulating a wide cross section with a total of 31 sectorial shocks. Equivalently, we think of these shocks as a way to depict impulse responses away from the regular simulation paths. In the graphs we use shaded areas to highlight the twenty quarters following the arrival of these two special shocks.

In the top-left panel of Figure 1(b) we show the path of output growth. Over the quarterly frequency, it is mainly driven by short-run shocks and it barely simultaneously responds to individual sectorial shocks. *Expected* output growth, instead, is quite sensitive to sectorial long-run growth dynamics as they diffuse across sectors (top-right panel). Since the diffusion of shocks through the economy is slow, the full response of aggregate expected growth manifests itself with a significant lag. As an example, consider the positive (negative) shock given to industry 1 (industry 11) at time 20 (time 80). The growth rate of industry 1 (industry 11) leads the peak (trough) of aggregate growth by $(N-1)/2 = 15$ quarters. The cash flow of industry 11 (industry 1) lags that of industry 1 (industry 11) by 10 periods.

As shown in the bottom panels of Figure 1(b), our LL indicator is able to correctly pick up leading cash flows. Although with some noise due to the small data window that we employ, the LL indicator of industry 1 starts to increase within a few quarters from the realization of our positive shocks. For about 20 quarters, industry 1 is correctly identified as strongly leading GDP growth. The same holds with industry 11, since it is identified as leading the recession episode occurring after period 80. Simultaneously, during this recession industry 1 is classified as lagging industry because its LL indicator declines.

Summarizing, even though all industries are all ex-ante identical, in our network they are ex-post either lagging or leading the growth cycle. Our lead-lag indicators can capture this feature in a very parsimonious and flexible way. We acknowledge that in very long samples a vector autoregression with time-varying coefficients may convey all of the relevant network information dynamics. In relatively short samples with a large cross section, however, estimating such a high-dimensional VAR with sufficient precision appears extremely challenging. We think of cross-correlograms as a useful non-parametric alternative tool.

3 Empirical Investigation

Data sources. In our empirical analysis, we use monthly stock returns from CRSP as well as the corresponding quarterly data from COMPUSTAT for the period from from 1972:01 to 2012:12. The quarterly data coverage in COMPUSTAT prior to 1972 is too limited for our investigation. We group firms into 30 industries following the classification scheme available on Kenneth French's website. We start by computing industry-level output by aggregating firms' operating income before depreciation and net of interest expenses, income taxes, and dividends (as in Acharya et al. (2014)). We also employ alternative measures in our robustness exercises, which we will describe in detail in the next sections. We use dummy variables to remove seasonality. We gather aggregate US consumption and output data from the National Income and Product Accounts (NIPA). All variables are seasonally adjusted and in real units. Inflation is computed using the Consumer Price Index (CPI).

LL indicators. For each industry, in each quarter we compute the $\pm$4-quarter cross-correlation between industry-level output growth and the domestic output growth using 20-quarter rolling windows. According to the methods described in the previous section, we then compute conditional quarterly lead-lag measures for each industry. This procedure generates a panel of industry-level lead-lag (LL) indicators spanning 41 years.

To provide economic guidance about our measure, in Figure 2 we report our industry-level weighted average LL indicators for the IT, the real estate, and the finance industries starting from 1995. We focus on these industries because they have been important drivers of the last two main economic cycles in the US, and hence they represent a natural reference point for our methodology.

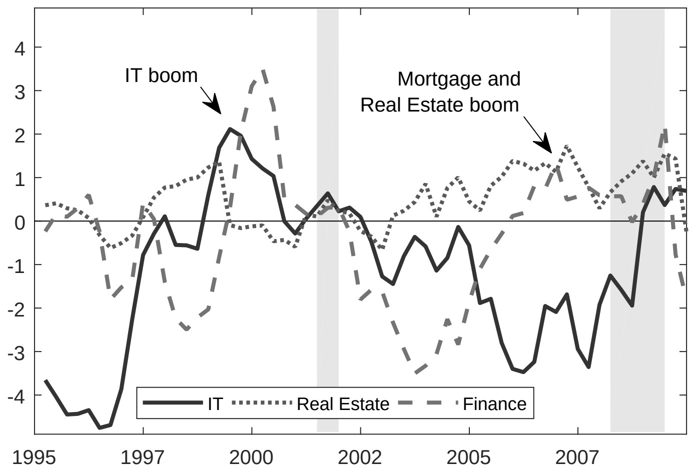


Fig. 2: Lead-Lag Indicator for Selected Industries

This figure depicts the lead-lag (LL) indicator for three major industries. The LL indicator is computed in two steps. First, for each industry, in each quarter we compute the ±4-quarter cross-correlation between industry-level output growth and the domestic output growth using 20-quarter rolling windows. Second, we compute the industry-level weighted average of leads and lags and assign it to the corresponding industry as its LL indicator. A positive (negative) LL indicator denotes an industry whose output growth leads (lags) GDP growth. Quarterly growth rates are adjusted for inflation and seasonality. Grey bars denote NBER recession periods.

We find it reassuring that our methodology detects several well-known economic patterns. For example, the IT industry became progressively more leading in the 1995-2000 subsample, that is, during the IT boom. The boom of the early 2000, instead, was led by real estate, with finance becoming progressively more leading after 2005 and during the Great Recession. We provide other interesting facts about our LL indicators in Appendix A and focus next on our time-series analysis.

3.1 Time-Series Analysis

Portfolio sorting and the LL factor. We start with the Fama-French 30-industry cross section. In each quarter, we sort firms grouped in our 30 industries according to their maximum correlation LL indicator value and divide them into three portfolios. Our lead (lag) portfolio contains the top 20% of leading (lagging) industries. In each quarter, each of these two portfolios represents at least 15% of total market capitalization, implying that our results are not driven by a fraction of small and potentially illiquid firms.

Table 1: Lead-Lag Portfolio Sorting (Max Correlation)

	Lead	Mid	Lag	LL	LL Strong
Average return	9.43***	6.03**	5.24*	4.20**	5.24***
	(2.27)	(2.76)	(3.04)	(1.79)	(1.96)
CAPM α	3.17***	−0.63	−1.79	4.96***	6.12***
	(1.05)	(0.47)	(1.30)	(1.89)	(1.95)
FF3 α	3.02***	−0.71	−1.66	4.68**	6.23**
	(1.16)	(0.54)	(1.43)	(2.08)	(2.49)

Notes: This table provides real annualized value-weighted returns of portfolios of firms sorted according to their industry-level lead-lag (LL) indicator. First, for each industry, in each quarter we compute the ±4-quarter cross-correlation between industry-level output growth and the domestic output growth using 20-quarter rolling windows. Second, we identify the lead or lag for which the maximum absolute cross-correlation is attained and assign it to the corresponding industry as its LL indicator. A positive (negative) LL indicator denotes an industry whose output growth leads (lags) GDP growth. Our Lead (Lag) portfolio contains the top (bottom) 20% of our leading industries. These portfolios represent at least 15% of the total market value in each quarter. All other firms are assigned to the middle (Mid) portfolio. The LL portfolio reflects a zero-dollar strategy long in Lead and short in Lag. In each portfolio, we identify the industries with the absolute value of correlation above the portfolio's median and group them in a subportfolio denoted as 'Strong'. The LL Strong portfolio represents a zero-dollar trading strategy long in Lead Strong and short in Lag Strong. Return data are monthly over the sample 1972:01–2012:12. Industry definitions are from Kenneth French's website. CAPM α (FF3 α) denotes average excess returns unexplained by the CAPM (Fama-French three-factor model). The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

For each portfolio, we compute value-weighted monthly returns and highlight the following relevant facts. First, we construct a lead-lag (LL) factor by considering the returns of a zero-dollar investment strategy long in the leading and short in the lagging portfolio. This strategy pays an average annualized excess return of 4.2%, which remains significant and sizeable even after adjusting the returns for either the CAPM or the FF3 factors (see the implied alphas in Table 1). In Appendix B, we show that these results continue to hold also when we consider different quantiles (with respect to the minimum share of market capitalization) for the formation of the lead and lag portfolios (see Table B1).

Second, within each portfolio we identify the industries whose absolute value of correlation with output is above the median. We group the above-median industries in subportfolios denoted as 'Strong', given that they feature a stronger and less noisy lead/lag connection with aggregate output. We then study the return of a zero-dollar investment strategy long

Table 2: Lead-Lag Portfolio Sorting Across LL-indicators

	Max Corr. LL	Industry-Weighted Avg. LL	Cross-Industr. LL
Volatility	11.52	11.15	12.30
Sharpe Ratio	0.36	0.24	0.32
CAPM α	4.96***	2.94*	4.09*
FF3 α	4.68**	2.95*	4.87**
Portfolio Turnover	0.13	0.08	0.11
Industry migration	1.0	0.7	0.8

This table provides real annualized value-weighted returns for a zero-dollar strategy long in Lead and short in Lag industries across three different ways to compute the lead-lag indicator. Turnover measures the percentage of industries entering or exiting from a portfolio. Industry migration measure the median number of times an industry moves across portfolios in a year. Return data are monthly over the sample 1972:01–2012:12. Industry definitions are from Kenneth French's website. CAPM α (FF3 α) denotes average excess returns unexplained by the CAPM (Fama-French three-factor model). The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

in Lead-Strong and short in Lag-Strong. We obtain even stronger results (see Table 1, right-most column). Untabulated results confirm that these empirical patterns are present also when we focus on equally weighted returns.

Third, these results are confirmed across our three ways to compute the LL indicator (see Table 2). The LL factor has a Sharpe ratio ranging from 0.25 to 0.35 and its alpha ranges from 3% to 4% after adjusting for either the CAPM or the FF3 factors. The average quarterly turnover is stable and very moderate at about 10%.[5] According to our methodology, industries move across portfolios at most once a year.

Granularity. We explore the role of granularity and report key results on the leading premium in Table 3. Specifically, we adopt our sorting procedure after grouping firms into 38 and 49 industries, respectively. We point out the existence of a relevant tension between number of industries and precision of our ranking. On the one hand, considering more

[5] In each quarter, we compute the market value of the firms that either exit or enter a given portfolio. We divide this number by two and report it as a fraction of the total market value. Expressing turnover in market value terms prevents our measure from being driven by many small industries frequently moving across portfolios.

Table 3: Lead-Lag Portfolio Sorting – 38 and 49 Industries

	Panel A: 38 industries		Panel B: 49 industries	
	LL	LL Strong	LL	LL Strong
Average return	3.16**	6.54**	4.31**	5.06**
	(1.57)	(2.93)	(2.11)	(2.57)
CAPM α	3.84**	6.94**	5.10**	5.99**
	(1.64)	(2.97)	(2.21)	(2.68)
FF3 α	3.55*	5.41*	4.61**	5.69**
	(2.00)	(3.17)	(2.25)	(2.62)
Turnover	0.11	0.07	0.11	0.08

Notes: This table provides real annualized value-weighted returns of portfolios of firms sorted according to their industry-level lead-lag (LL) indicator. The formation of the portfolios is identical to that described in the notes to table 1. In contrast to our benchmark specification that uses a 30-industry classification, this table documents results for 38 industries (Panel A) and 49 industries (Panel B). The LL portfolio reflects a zero-dollar strategy long in Lead and short in Lag. In each portfolio, we identify the industries with the absolute value of correlation above the portfolio's median and group them in a subportfolio denoted as 'Strong'. The LL Strong portfolio represents a zero-dollar trading strategy long in Lead Strong and short in Lag Strong. Turnover measures the percentage of industries entering or exiting from a portfolio. Return data are monthly over the sample 1972:01–2012:12. Industry definitions are from Kenneth French's website. CAPM α (FF3 α) denotes average excess returns unexplained by the CAPM (Fama-French three-factor model). The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

industries enables us to gain more power from the cross section. On the other, considering a more granular definition of industries makes our estimation of industry-level leads and lags more noisy and hence it makes our sorting less precise. We find it encouraging that our results on the leading premium are confirmed when working with both 38 and 49 industries. We present robustness analyses with respect to an alternative way to measure leads and lags in the appendix in Table B2.

Size and Book-to-Market. We double-sort the firms belonging to our lead and lag portfolios with respect to either their book-to-market (B/M) ratios, or their market capitalization (Size). As in Fama and French (2012), we choose the 30th and 70th percentiles of the book-to-market distribution as cutoff points to obtain low, medium, and high book-to-market portfolios. We do the same with respect to size and report our main results in Table 4.

Our leading premium is sizeable and statistically significant for both low and medium B/M firms. Among value firms, the premium is positive but measured with noise. This may

Table 4: Lead-Lag Portfolio – Double Sort

	Panel A: LL and B/M			Panel B: LL and Size		
	Low	Mid	High	Small	Mid	Large
Average return	3.53*	6.07**	1.88	3.93	3.27	4.40**
	(1.89)	(2.45)	(1.90)	(2.48)	(2.16)	(1.85)
CAPM α	4.37**	5.92**	1.99	3.30	3.31	5.21***
	(2.00)	(2.59)	(1.95)	(2.52)	(2.29)	(1.96)
FF3 α	4.40*	4.91**	1.90	1.38	1.73	4.92**
	(2.41)	(2.28)	(1.84)	(2.91)	(2.26)	(2.21)

Notes: This table provides two decompositions of the real annualized value-weighted returns of the LL portfolio constructed as described in table 1. In panel A, we decompose the LL return by double-sorting firms according to their book-to-market (B/M) ratio within the Lead and Lag portfolios. Our cutoff points are the 30th and 70th percentiles of the B/M distribution within each portfolio. Analogously, in panel B we decompose the LL return by double-sorting firms according to their market capitalization (Size) within the Lead and Lag portfolios. Our cutoff points are the 30th and 70th percentiles of the Size distribution within each portfolio. Return data are monthly over the sample 1972:01–2012:12. Industry definitions are from Kenneth French's website. CAPM α (FF3 α) denotes average excess returns unexplained by the CAPM (Fama-French three-factor model). The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

be due to the fact that value firms in both the lead and lag portfolios count for just 2% of total market value, a very small fraction. Our leading premium is a broad phenomenon in the cross section of firms, as it applies to 80% of our firms that, in turn, represent between 28% and 38% of total market value. In a similar spirit, we note that our leading premium is not driven by small-cap firms, since our lead-lag structure in the cross section of industry cash-flows is mainly generated by large firms.

All of these results hold regardless of whether we use fixed 30%-70% cutoff levels computed from the full cross section of B/M and Size, or focus on the distribution of B/M and Size within each LL-sorted portfolio.

Given these results, it is natural to ask whether there is some fundamental difference across leading and lagging industries. Table 5 addresses this question by looking at investment intensity and dividend payouts. From a statistical point of view, firms in leading industries have an average investment intensity comparable to that of lagging firms. Lagging firms, however, adjust their investments more (as indicated by a higher standard deviation of the ratio of investment to total assets, $StD(I/A)$), and their dividends are less exposed

Table 5: Investment Activity of Leading/Lagging Industries

	Leading Portfolio	**Lagging Portfolio**	p**-value**
	Investment intensity		
Mean(I/A)	1.37	1.75	0.465
Std(I/A)	2.01	5.36	0.000
	Dividends Growth		
Total Volatility	0.09	0.12	0.006
β_X (long-run risk exposure)	3.00	−1.27	0.030

Notes: This table provides statistics for both dividends growth and investmment intensity leading and lagging industries identified using our benchmark strategy. We measure investments by capital expenditures (CAPX) over total assets. Balance sheet data are quarterly over the sample 1972Q1–2012Q4. Industry definitions are from Kenneth French's website. The rightmost column *'p-value'* reports the p-value for the test of difference between statistics for leading and lagging industries with the null hypothesis being that the statistics across the groups are equal. The long-run exposure coefficient refers to the following regression:

$$\Delta d_{t+1} = \beta_0 + \beta_X x_t + resid_t,$$

where x_t is the expected component of consumption growth identified as described in section 4.

to consumption long-run risk (we detail the identification of consumption long-run risk in Section 4). These results are broadly consistent with the idea that lagging firms have time to process information about future fluctuations and use information to both revise their investment plans and smooth their dividends for the long-run.[6]

LL's additional informativeness. In an economy in which shocks diffuse immediately across sectors, or, more broadly, the network of industries is not very relevant for the diffusion of shocks, our lead-lag factor should not provide additional information once we control for other aggregate factors. In this section, we use standard time-series tests to formalize further the disconnect between our leading premium and other well-known risk factors. We interpret these results as suggesting that existing risk factors are not enough to fully capture the role of the many shocks that affect our granular cross section of industries.

Henceforth, we denote the market, size, and value factors as, MKT, SMB, and HML, respectively. We consider also other financial factors that may be related to cyclical economic fluctuations, such as investment minus consumption proposed by Kogan and Papanikolaou

[6]We thank Laura Veldkamp for this insight. These results hold also when we exclude financial firms. Dividends growth rates are seasonally adjusted and expressed as year-over-year quarterly rates.

Table 6: **The Disconnect between LL and Other Factors**

	(1)	(2)	(3)	(4)	(5)	(6)
α_{LL}	4.96***	4.68**	4.61**	4.55**	3.74**	4.22**
	(1.89)	(2.08)	(2.00)	(1.90)	(1.73)	(1.94)
MKT	−0.13*	−0.13	−0.07	−0.12*	−0.11*	−0.11
	(0.08)	(0.09)	(0.08)	(0.07)	(0.07)	(0.07)
SMB		0.04	0.13	0.05	0.02	0.07
		(0.08)	(0.10)	(0.07)	(0.07)	(0.09)
HML		0.04	−0.06	0.05	0.06	−0.06
		(0.16)	(0.13)	(0.13)	(0.13)	(0.14)
IMC			−0.26***			
			(0.09)			
DUR				−0.03		
				(0.08)		
iMOM					0.18**	
					(0.08)	
iBAB						0.28***
						(0.10)
Adj. R^2	0.03	0.03	0.08	0.03	0.08	0.08
# Obs.	492	492	492	492	492	492

Notes: This table reports the results from regressing the LL factor constructed as in table 1 on other financial factors. Here, we consider market (MKT), size (SMB), value (HML), investment minus consumption by Kogan and Papanikolaou (2014) (IMC), durability by Gomes et al. (2009) (DUR), industry momentum by Moskowitz and Grinblatt (1999) (iMOM), and industry betting-against-beta by Asness et al. (2014) (iBAB) factors. Newey-West adjusted standard errors are reported in in parentheses. Monthly data start in 1972:01 and end in 2012:12.

(2014) (IMC), durability suggested by Gomes et al. (2009) (DUR), industry momentum constructed in the spirit of Moskowitz and Grinblatt (1999) (iMOM(6,6)), and industry betting-against-beta as suggested by Asness et al. (2014) (iBAB).

We show our estimates for the following regression:

$$LL_t = \alpha_{LL} + \gamma F_t + \varepsilon_t, \tag{1}$$

where F_t comprises the factors mentioned above. Across all specifications, the intercept remains statistically significant and sizable, and the implied adjusted R-squared are smaller than 10%. All of these results confirm that (i) our leading premium is mostly unrelated to the FF3 factors and durability; and (ii) our factor goes beyond the role played by investment shocks, industry momentum, and industry-level betting against the beta.[7] Untabulated

[7]The negative beta assigned to the IMC factor is fully consistent with Figure A1, as industries producing investment goods tend to lag the cycle.

Table 7: The Disconnect between LL and Other Factors (II)

FF5		HXZ q-factors		Carhart MOM			
α_{LL}	4.00**	α_{LL}	3.96**	α_{LL}	4.20**	5.17***	4.98**
	(2.24)		(2.40)		(2.07)	(2.06)	(2.35)
MKT	−0.08	MKT	−0.11*	MKT		−0.14**	−0.10
	(0.07)		(0.06)			(0.07)	(0.08)
SMB	−0.06	ME	−0.04	MOM	0.12	0.10	0.11
	(0.10)		(0.07)		(0.09)	(0.09)	(0.08)
HML	−0.10	I/A	0.03	SMB			−0.14*
	(0.18)		(0.19)				(0.08)
RMW	0.32***	ROE	0.28**	HML			0.05
	(0.10)		(0.13)				(0.14)
CMA	0.27						
	(0.22)						
Adj. R^2	0.06	Adj. R^2	0.06	Adj. R^2	0.02	0.04	0.05
# Obs.	492	# Obs.	492	# Obs.	492	492	492

Notes: This table reports the results from regressing the LL Strong factor constructed as detailed in table 1 on Fama and French 5 factors (FF5), the Hou et al. (2015a, b) q-factors, and the Carhart momentum factor (MOM). Newey-West adjusted standard errors are reported in parentheses. Monthly data start in 1972:01 and end in 2012:12. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Here, we perform one-sided test against the hypothesis $H_0 : \alpha < 0$. For factors loadings the significance corresponds to the two-sided tests.

results confirm that these conclusions can be obtained also when considering more granular cross sections with either 38 or 49 industries. Our results apply also when using different holding and formation periods for the construction of iMOM (see Table B3 in the appendix). Furthermore, our LL factor continues to have relevant information when we run our time-series tests on principal components that are extracted from all of these factors and explain up to 93% of their variation (see Tables B4 and B5).

We deepen our analysis by exploring the connection between the leading factor, the q-factors of Hou et al. (2015a, b), the FF5 factors of Fama and French (2015), and the Carhart (1997) momentum factor. As shown in Table 7, the alpha associated to our leading factor remains sizeable and significant across all cases considered. Even though our leading factor is related to cyclical measures like ROE and RMW, it is mostly unexplained by them.

We also include a dummy for NBER recessions and document that the leading premium is not a recession-driven phenomenon (see Table B6 in the appendix). Hence our factor is distinct from that in Lettau et al. (2014). In Table B7, we show that our results are not subsumed by either the announcement risk factor of Savor and Wilson (2016) or the production network premium identified by Gofman et al. (2017). Our results continue to hold also when we consider aggregate consumption growth as opposed to GDP growth (see Table B8).

Predictability of macroeconomic aggregates. In order to test the economic significance of our findings, we assess whether the aggregate valuation ratio of our leading firms has predictive power on industrial production and unemployment in addition to that of classical predictors. Specifically, we construct the price-dividend ratio for both the aggregate stock market and our leading portfolio and use these two ratios in standard forecasting regressions.

We report our findings in Table 8 and note two relevant results. First, our leading price-dividends ratio exhibits significant predictive power for both industrial production and employment. This result obtains while controlling for other well-known predictive factors, such as the aggregate price-dividends ratio, a measure for the aggregate credit spread, inflation, and the federal funds rate. Second, the predictive power of the leading price-dividends ratio is increasing in the horizon of our regressions in terms of both coefficient magnitude (γ_h) and contribution to the adjusted R^2. This contribution is measured by the difference between the adjusted R^2 values with and without the leading price-dividend ratio included in the regression. We note that we do not focus on cumulative growth rates and hence we are not exposed to the potential problems pointed out by Valkanov (2003). Our estimates are adjusted for the Stambaugh (1986) bias, and our inference is based on a bootstrap procedure that mitigates the issues pointed out by Torous et al. (2004).

3.2 Cross-Sectional Tests

The goal of this section is twofold. On the one hand, in the spirit of the empirical asset pricing literature, we want to confirm that our new factor conveys additional information for the cross-section of equity returns and is not just a 'lucky factor'. On the other hand, our cross-sectional investigation is necessary to better disentangle the portion of our leading premium that is associated with advance information and cannot be attributed to exposure

Table 8: Predictive Properties of Leading Price-Dividend Ratio

Industrial production growth				
	$h=1$	$h=2$	$h=3$	$h=4$
Eq. (1)-(3), γ_h	0.023***	0.032***	0.040***	0.046***
	(0.005)	(0.007)	(0.008)	(0.008)
Adj. R^2	0.467	0.188	0.040	0.020
Adj. R^2*	0.461	0.176	0.017	−0.013
Eq. (2), γ_h	0.022***	0.029***	0.037***	0.043***
	(0.006)	(0.007)	(0.007)	(0.007)
Adj. R^2	0.493	0.265	0.169	0.167
Adj. R^2*	0.488	0.255	0.149	0.138
Unemployment growth				
	$h=1$	$h=2$	$h=3$	$h=4$
Eq. (1)-(3), γ_h	−0.080***	−0.122***	−0.151***	−0.162***
	(0.017)	(0.021)	(0.024)	(0.023)
Adj. R^2	0.538	0.279	0.107	0.047
Adj. R^2*	0.527	0.255	0.066	−0.001
Eq. (2), γ_h	−0.081***	−0.112***	−0.139***	−0.151***
	(0.020)	(0.023)	(0.025)	(0.023)
Adj. R^2	0.557	0.336	0.208	0.172
Adj. R^2*	0.547	0.316	0.174	0.130

Notes: This table reports loadings of industrial production growth and unemployment growth h quarters ahead on the price-dividend ratio of the leading portfolio. In particular, we estimate predictive regressions of the form:

$$\Delta g_{t+h} = \gamma_0 + \gamma_h pd_t^{lead} + \delta pd_t^{MKT} + \alpha \Delta g_{t-1} + \varepsilon_{t+h},\ h = 1,..,4 \tag{1}$$

$$\Delta g_{t+h} = \gamma_0 + \gamma_h pd_t^{lead} + \delta pd_t^{MKT} + \alpha \Delta g_{t-1} + \text{controls} + \epsilon_{t+h},\ h = 1,..,4 \tag{2}$$

$$pd_t^{lead} = \rho_0 + \rho_1 pd_{t-1}^{lead} + u_t \tag{3}$$

where Δg_{t+h} is the h-quarter ahead one-period growth rate of industrial production and unemployment. In the regressions, we control for the $(t-1)$-growth rate, Δg_{t-1}. The set of controls includes the default spread, inflation, and federal fund rate. Estimated coefficients have been adjusted with the Stambaugh bias correction. Bootstrap standard errors are in parentheses. *Adj* R^2 * denotes adjusted R-squared for an equivalent regression where pd^{lead} is excluded. The quarterly data start in 1973:Q1 and end in 2012:Q4. One, two, and three asterisks denote significance at the 10%, 5%, and 1% level, respectively.

to other factors connected to cyclical economic activity.

Pricing tests. We use GMM to estimate the following linear pricing model

$$R_{i,t}^{ex} = a_i + \beta_i \cdot F_t + u_{i,t} \tag{2}$$

$$E[R_{i,t}^{ex}] = \beta_i \lambda + v_i, \tag{3}$$

in which R^{ex} denotes excess returns, i indexes the test assets, and the β and λ coefficients measure the exposure of returns to and the market price of risk of our factors, F_t, respectively. As in Cochrane (2005), we represent the discount factor as $m_t = \overline{m} - bf_t$, so that

$$b = E(f_t f_t')^{-1}\lambda. \tag{4}$$

Efficient standard errors are corrected for autocorrelation and heteroskedasticity following Newey and West (1987).[8]

We first run a conventional analysis across many different cross sections of test assets both for robustness and to address the criticism of Lewellen et al. (2010) related to the strong factor structure of the size and book-to-market cross sections. In the ensuing analysis individual stocks are sorted with respect to their conditional betas for the LL factor. In both steps, we highlight the implied time premium.

Conventional test assets. In Table 9, we report our results for both the market prices of risk and the implied stochastic discount factor loadings associated with our four factors, that is, FF3 plus the LL factor. Since we take the concerns about spurious inference seriously, we also report the cross sectional improvement in GLS R^2 (GLS R^2+, see Lewellen et al. (2010)) and the mean scaled intercept (SI, see Harvey and Liu (2018)) statistics.[9]

[8] We use a two-step procedure. In the first iteration, we set the weighting matrix for the moment conditions equal to the identity matrix. In the second iteration, we use the optimal weighting matrix from our first iteration.

[9] We follow Harvey and Liu (2018) in aggregating the results from 10,000 bootstrap samples of the entire cross section with replacement.

Table 9: Prices of Risk and Pricing Kernel Loadings

Cross Section (# portfolios)	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{LL}	b_{MKT}	b_{SMB}	b_{HML}	b_{LL}	GLS R^2+	SI
30 industries	0.57***	−0.23	−0.02	0.45**	0.04***	−0.04	0.00	0.05***	0.30	−0.084
	(0.22)	(0.21)	(0.23)	(0.20)	(0.01)	(0.02)	(0.03)	(0.02)		[0.03]
38 industries	0.57***	−0.16	0.05	0.42**	0.04***	−0.03	0.02	0.05***	0.27	−0.053
	(0.22)	(0.19)	(0.25)	(0.20)	(0.01)	(0.02)	(0.03)	(0.02)		[0.05]
49 industries	0.59***	−0.24	−0.07	0.49**	0.04***	−0.04*	0.00	0.05**	0.18	−0.070
	(0.21)	(0.20)	(0.24)	(0.24)	(0.01)	(0.02)	(0.03)	(0.02)		[0.01]
BE/ME and Size (25)	0.44**	0.17	0.46***	0.37**	0.04***	0.02	0.07***	0.04***	0.08	−0.032
	(0.22)	(0.15)	(0.17)	(0.15)	(0.01)	(0.02)	(0.02)	(0.01)		[0.07]
BE/ME and OP (25)	0.45**	−0.12	0.52***	0.30**	0.04***	−0.01	0.07***	0.03**	0.21	−0.026
	(0.22)	(0.27)	(0.19)	(0.15)	(0.01)	(0.03)	(0.02)	(0.01)		[0.10]
BE/ME and INV (25)	0.52**	−0.16	0.31*	0.36**	0.04***	−0.02	0.05**	0.04***	0.20	−0.003
	(0.22)	(0.25)	(0.18)	(0.15)	(0.01)	(0.03)	(0.02)	(0.01)		[0.04]
OP and INV (25)	0.48**	−0.37	0.66***	0.47***	0.05***	−0.04	0.08***	0.05***	0.10	−0.076
	(0.22)	(0.25)	(0.22)	(0.16)	(0.01)	(0.03)	(0.03)	(0.01)		[0.08]
Size and OP (25)	0.44**	0.05	0.86**	0.42***	0.05***	0.01	0.12**	0.04***	0.16	−0.079
	(0.22)	(0.15)	(0.40)	(0.16)	(0.01)	(0.02)	(0.05)	(0.01)		[0.17]
Size and INV (25)	0.48**	0.07	0.77***	0.35**	0.05***	0.01	0.11***	0.04***	0.06	−0.093
	(0.22)	(0.15)	(0.20)	(0.15)	(0.01)	(0.02)	(0.02)	(0.01)		[0.08]
Size and Beta (25)	0.43**	0.12	0.76**	0.36**	0.04***	0.02	0.11***	0.04***	0.12	−0.168
	(0.22)	(0.15)	(0.33)	(0.15)	(0.01)	(0.02)	(0.04)	(0.01)		[0.09]
Size and LT Reversal (25)	0.50**	0.12	0.54***	0.36**	0.04***	0.01	0.08***	0.04***	0.13	−0.114
	(0.22)	(0.16)	(0.20)	(0.15)	(0.01)	(0.02)	(0.02)	(0.01)		[0.01]
Size, BE/ME, INV, OP (40)	0.49**	0.07	0.34**	0.43***	0.04***	0.00	0.05***	0.05***	0.10	−0.061
	(0.22)	(0.15)	(0.17)	(0.16)	(0.01)	(0.02)	(0.02)	(0.01)		[0.03]
Size, BE/ME, INV, OP, MOM (50)	0.49**	0.09	0.23	0.86***	0.04***	0.00	0.04*	0.09***	0.07	−0.090
	(0.22)	(0.15)	(0.18)	(0.17)	(0.01)	(0.02)	(0.02)	(0.02)		[0.03]

Notes: This table presents factor risk premia and the exposures of the pricing kernel to FF3 (MKT, SMB, HML) and our lead-lag factor (LL). We employ the generalized method of moments (GMM) to estimate the linear factor model stated in equations (2)–(4). GLS R^2+ denotes the improvement in GLS R^2 achieved by adding the LL factor to the FF3 factors. *SI* denotes the average scaled intercept of Harvey and Liu (2018). Associated $p-$values are in squared brackets. Our set of test assets consists of 30-, 38-, and 48-industry portfolios; portfolios sorted on book-to-market (BE/ME), market capitalization (Size), operating profits (OP), and investments (INV); double-sorted portfolios sorted on size and long-term (LT) reversal. Our monthly sample is 1:1972–12:2012. The numbers in parentheses are Newey and West (1987) standard errors. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

We find that both the factor risk premium λ_{LL} and the pricing kernel loading b_{LL} are statistically significant at the 5% and often 1% level. The cross sectional R^2 improvement is sizeable and particularly so for the industry cross section. The $p-$value of the SI statistics is always smaller or equal to 10%, implying that we can reject the null hypothesis that the LL factor is a lucky factor.

Hence, these tests confirm that our LL factor is both relevant and required when it comes to pricing the cross sections equity returns, including those in which portfolios are sorted with respect to investment (INV), operating profits (OP), long-term reversal (LT Reversal), and momentum (MOM).[10] In Appendix B, we show that these results are still significant, albeit at a higher significance level, when we add either momentum or durability to set of risk factors to study the cross section of industries (see Table B9).

In Table 10, we report for each cross-section the maximum spread in the portfolio exposures to the LL factor and a measure of the implied timing premium. On average, the timing premium is about 1.5% per year, i.e., about 35% of our measured leading premium (see table 1).

Portfolios sorted on firm-level LL-exposure. Computing cross-correlograms on firm-level cash flows is impractical because cash flows are too noisy. Consistent with prior literature, we use the firm-level returns exposure to our return-based factor to proxy the extent to which a firm leads/lags the cycle.

Specifically, we start by taking our LL factor from our benchmark procedure that considers 30 industries. For each firm, we then compute its conditional exposure to the LL factor ($\beta_{LL,i,t}$) over a rolling-window that includes the past 60 months. We control for the FF3 factors in the regression and sort firms according to their $\beta_{LL,i,t}$ into 30 portfolios that we use as test assets. By grouping together all firms with strongly positive (negative) exposure, this procedure bundles the most leading (lagging) firms in the economy across industries. These portfolios are re-formed once a year.

[10]Fama and French (1993) do not estimate market prices of risk as we do. We run the Fama-MacBeth regressions replication code choosing our industry portfolios as test assets. In this cross section, we obtained poorly identified, and often negative, market price of risk for both SMB and HML.

Table 10: Disentangling Timing Premium from Leading Premium

	Max(β_{LL})-Min(β_{LL})	$\lambda_{LL}\cdot$(Max(β_{LL})-Min(β_{LL}))
30 industries	0.588	3.18
38 industries	0.522	2.63
49 industries	0.665	3.91
BE/ME and Size (25)	0.082	0.37
BE/ME and OP (25)	0.338	1.22
BE/ME and INV (25)	0.183	0.79
OP and INV (25)	0.288	1.62
Size and OP (25)	0.182	0.92
Size and INV (25)	0.145	0.61
Size and Beta (25)	0.324	1.40
Size and LT Reversal (25)	0.183	0.79
Size, BE/ME, INV, OP (40)	0.215	1.11
Mean	0.310	1.55
Median	0.252	1.16

Notes: This table presents spreads in test assets' exposures to the LL factor β_{LL}, Max(β_{LL})-Min(β_{LL}), together with the product of these spreads and the corresponding factor risk premia, λ_{LL}(Max(β_{LL})-Min(β_{LL})). We employ the generalized method of moments (GMM) to estimate the linear factor model stated in equations (2)–(3). All returns are monthly from January 1972 through December 2012. At the bottom of the table, we report sample mean and median of the quantities.

Our results are reported in Table 11 (top portion of each panel) and confirm what we had found in our previous analysis, namely that the LL factor is priced and it enters the discount factor in an independent and significant way. Furthermore, the implied size of the timing premium is about 1.8% per year, as indicated by the values in the last column of Panel A.

We then turn our attention to firm heterogeneity within industries. We focus on 38 (49) industries and sort firms within each industry in 3 (2) portfolios according to their $\beta_{LL,i,t}$ exposure.[11] This procedure enables us to have a larger cross section of test assets and confirms that the LL factor is still priced in the cross-section. To be conservative, we use the top- and bottom-20% exposure coefficients from our cross sections to imputed the timing premium. We confirm the timing premium ranges from 1.3% to 2% per year.

[11] When we compute the $\beta_{LL,i,t}$ with 38 (49) industries we also use the benchmark LL factor that we obtained working with 30 industries.

Table 11: Prices of Risk and Pricing Kernel Loadings – LL Cross Section

Panel A: $E[R_i^{ex}] = \beta_{MKT}\lambda_{MKT} + \beta_{SMB}\lambda_{SMB} + \beta_{HML}\lambda_{HML} + \beta_{LL}\lambda_{LL}$				
λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{LL}	$\left(\overline{\beta}_{LL} - \underline{\beta}_{LL}\right)\lambda_{LL}$
30 LL-portfolios				
0.64***	0.82	0.49	1.02*	1.77
(0.19)	(0.57)	(0.39)	(0.53)	
38 Industry × 3 LL-portfolios				
0.72***	0.25	-0.22	0.52*	1.29
(0.19)	(0.27)	(0.19)	(0.28)	
49 Industry × 2 LL-portfolios				
0.60***	-0.14	0.14	0.75*	2.09
(0.18)	(0.21)	(0.26)	(0.40)	

Panel B: $m_t = \overline{m} - b_{MKT}MKT_t - b_{SMB}SMB_t - b_{HML}HML_t - b_{LL}LL_t$			
b_{MKT}	b_{SMB}	b_{HML}	b_{LL}
30 LL-portfolios			
0.06***	0.10	0.10**	0.12**
(0.02)	(0.06)	(0.05)	(0.06)
38 Industry× 3 LL-portfolios			
0.05***	0.01	0.00	0.07**
(0.01)	(0.04)	(0.03)	(0.03)
49 Industry× 2 LL-portfolios			
0.06***	-0.02	0.03	0.09**
(0.01)	(0.03)	(0.03)	(0.04)

Notes: This table presents factor risk premia and the exposures of the pricing kernel to the FF3 factors (MKT, SMB, HML) and our lead-lag factor (LL). We employ the generalized method of moments (GMM) to estimate the linear factor model stated in equations (2)–(3). Using a linear projection of the stochastic discount factor m on the factors ($m = \overline{m} - f'b$), we determine the pricing kernel coefficients as $b = E[ff']^{-1}\lambda$. We use portfolios based on the individual firms' exposures to the LL factor ($\beta_{LL,i,t}$) estimated over previous 60 months as our test portfolios. The top section of each panel presents results for 30 lead-lag portfolios. In the middle (bottom) section the test portfolios are constructed by sorting firms on their $\beta_{LL,i,t}$ within each of 38 (49) industries into 3 (2) subgroups. $\overline{\beta}_{LL}$ ($\underline{\beta}_{LL}$) denotes the top (bottom) quintile of the LL-betas distribution. Our sample consists of monthly returns for test portfolios from January 1972 through December 2012. The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

3.3 Further Robustness Checks

In section B.1 of the appendix, we carry out several robustness tests relevant for our empirical findings. We start by assessing alternative measures for our lead/lag indicator. We then consider an alternative way to correct for seasonality and a sorting procedure based on Granger causality. All results are reported in Table B10.

We consider leads and lags of other cash-flows like, for example, dividends, operating income, capital expenditures and asset growth and confirm that leading firms bear a higher cost of equity. We also show that looking at leading and lagging firms is different from sorting firms according to their past cash-flow growth and creating a winners-minus-losers (WML) strategy. We show that our findings are robust to forming our lead-lag portfolio at an annual frequency, but they vanish if we proceed with an unconditional sorting done over the entire sample, consistent with the diffusion model presented in section 2.1 in which all industries are ex-ante identical.

4 An Equilibrium Model for the Leading Premium

By no-arbitrage our leading premium is connected to the spread between the equity yield curve and the bond yield curve (see appendix C). Equivalently, the leading premium is partially a reflection of the timing premium. As a result, any equilibrium asset pricing model able to deliver a substantial timing premium can produce our empirical findings. Given our empirical evidence on long-run dividends growth from Section 3, we focus on an equilibrium model featuring two main elements: (a) an information structure affected by leads and lags of long-run cash flows growth; and (b) preferences sensitive to the timing of information about future growth.

Specifically, we assume that the representative agent has Epstein and Zin (1989) preferences, i.e.,

$$U_t = \left[(1-\delta)C_t^{1-\frac{1}{\psi}} + \delta E_t\left[U_{t+1}^{1-\gamma}\right]^{\frac{1-\frac{1}{\psi}}{1-\gamma}}\right]^{\frac{1}{1-\frac{1}{\psi}}}$$

and her stochastic discount factor is

$$M_t = \delta e^{-\frac{1}{\psi}\Delta c_t}\left(\frac{U_t}{E_{t-1}[U_t^{1-\gamma}]^{\frac{1}{1-\gamma}}}\right)^{1/\psi-\gamma}.$$

In this economy, there are three fundamental cash flows: consumption, C; a redundant cash flow that provides anticipated information, D^{lead}; and a lagged redundant cash flow, D^{lag}. We assume that the following holds:

$$
\begin{aligned}
\Delta c_{t+1} &= \mu + x_{t-j_c} + \varepsilon^{c}_{t+1} && (5)\\
x_{t+1} &= \rho x_t + \varepsilon^{x}_{t+1} && (6)\\
\Delta d^{lead}_{t+1} &= \mu + \phi^{lead}_{x} x_t + \phi^{lead}_{0} \varepsilon_{c,t+1} + \varepsilon^{d,lead}_{t+1} && (7)\\
\Delta d^{lag}_{t+1} &= \mu + \phi^{lag}_{x} x_{t-j_d} + \sum_{f=0}^{j_{lag}} \phi^{lag}_{f} \varepsilon_{c,t+1-f} + \varepsilon^{d,lag}_{t+1}, && (8)
\end{aligned}
$$

where

$$
v_{t+1} = \begin{pmatrix} \varepsilon^{c}_{t+1} \\ \varepsilon^{x}_{t+1} \\ \varepsilon^{d,lead}_{t+1} \\ \varepsilon^{d,lag}_{t+1} \end{pmatrix} \sim \mathcal{N}.i.i.d.(0, \Sigma), \quad \text{and } \Sigma = diag(\sigma^2_c, \sigma^2_x, \sigma^2_{d,lead}, \sigma^2_{d,lag}).
$$

According to this law of motion, the leading portfolio has predictive power for expected consumption growth j_c periods ahead, that is, $E_t[\Delta c_{t+1+j_c}] = x_t$. For the lagged cash flows, the time lag on the long-run component is denoted by j_d. We also allow the agent to have advance information with respect to the exposure of the lagged cash flow to short-run consumption shocks over a maximum time horizon of j_{lag} periods. We do this to be consistent with the data, but it is not the main driver of our results.

At this point, we must clarify that this exercise has the sole purpose to assess the potential of this class of models to produce a substantial timing and leading premium. Since we are completely abstracting from network connections across firms and we work with managed portfolio cash flows, a good performance of our economy must be interpreted as an upper bound on what this class of models could deliver in a fully fledged network model.

The endogenous returns associated with this log-linear setting are reported in Appendix E. In what follows, we focus on the procedure that we use to calibrate these portfolio cash flows.

Calibration Strategy. Quarterly consumption data are from the BEA and include non-durables and services. To identify x_{t-j_c}, we run a standard forecasting regression using the thirteen factors formed by Jurado et al. (2015) and represent the estimated long-run risk component as an AR(1) process, consistent with Equation (6).[12] This procedure enables us to identify both long-run ($\epsilon_{x,t}$) and short-run ($\epsilon_{c,t}$) consumption news.

We compute the dividends paid out by both our lead and lag portfolios and aggregate them to a quarterly frequency.[13] We deflate them using quarterly US CPI and then regress the growth rates of these cash flows on leads and lags of both short- and long-run consumption news, consistent with Equations (7)–(8). We use adjusted R^2 to optimally pin down the maximum number of leading/lagging periods, as detailed in Appendix D. We set statistically insignificant coefficients to zero.

We summarize our main results in Table 12. The consumption long-run component lags that of the leading cash flow by 27 quarters ($j_c = 81$ months). The long-run component of the cash flow of the lagged portfolio lags by 47 quarters ($j_d = 141$ months). To be consistent with the data, we also allow this cash flow to load on lagged short-run consumption shocks. According to our results, anticipated information on these shocks plays a very marginal role (the estimated ϕ_f^{lag} coefficients can be found in Table D1 in the appendix).

The data suggest that the dividends of the leading portfolio tend to be more exposed to long-run growth news than those of the lagged portfolio. This fact is consistent with the view that lagging firms may use advance information to smooth their long-run dividend growth. Consistent with these results, we set $\phi_x^{lead} = 8.60$ and $\phi_x^{lag} = 6.39$. The relevance of this observation is twofold. First, we properly control for heterogeneous exposure to shocks,

[12] The point estimate of ρ is corrected for the small-sample bias (Kendall (1954)):

$$\mathbb{E}\left(\hat{\rho} - \rho\right) = -\frac{(1 + 3\hat{\rho})}{n}.$$

[13] Let $R_{p,t}^{ex}$ and $R_{p,t}^{cum}$ represent the ex- and cum-dividend returns of portfolio p. Let $V_{p,t}$ be the ex-dividend value of the investment strategy in portfolio p at time t. Dividends $D_{p,t}$ are then computed recursively:

$$\begin{aligned} D_{p,t} &= V_{p,t-1}(R_{p,t}^{cum} - R_{p,t}^{ex}) \\ V_{p,t} &= V_{p,t-1} R_{p,t}^{ex}, \end{aligned}$$

assuming $V_{p,0} = 1$.

as suggested by Bansal et al. (2005). Second, after accounting for heterogeneity in exposure we can isolate the role of heterogeneity in the timing of exposure, i.e., the relevance of the pure timing premium.

The properties of aggregate consumption growth are consistent with both prior findings and our own estimation results. We set the monthly persistence of long-run risk to 0.9, a value lower than that in Bansal and Yaron (2004) and consistent with our empirical confidence interval.[14] The volatility of the long-run news, σ_x, is calibrated to be consistent with the R^2 that we obtain from estimating equation (5). The volatility of the consumption short-run shock is calibrated to a low level, consistent with the fact that we use post-1972 data, i.e., observations from a period of great moderation.

Results. Under our benchmark calibration, we set the preference parameters as in Bansal and Yaron (2004). Specifically, the relative risk aversion (γ) is set to 10; the intertemporal elasticity of substitution (ψ) is 1.5; and the subjective discount rate (δ) is set to 0.99 to keep the risk-free rate to a low level.

Our benchmark model produces an annualized LL premium of 3.10%, a number consistent with our empirical evidence. In order to look at the composition of the leading premium, we remove advance information by setting $j_c = j_d = 0$ and hence determine the portion of the premium solely driven by heterogeneous exposure ($\phi_x^{lead} > \phi_x^{lag}$). We find that heterogeneous exposure generates a premium of 1.65%. Thus the pure timing premium is 1.45% per year, a figure consistent with our estimates range.

These results are mostly driven by information about long-run growth, as can be seen by comparing our benchmark setting with the case in which we remove short-run risk exposure from the cash flow of both the leading and the lagging portfolios ($\phi_f^p = 0$ for all f and $p \in \{lead, lag\}$). In this case, our results are actually stronger, as the LL premium is even closer to its empirical counterpart.

We also compute the utility-consumption ratio associated with these scenarios. By com-

[14] We estimate the quarterly persistence parameter ρ and report the inference for $\rho^{1/3}$. Standard errors are computed using the delta method.

paring these ratios in log units, we can compute welfare benefits in terms of percentage of lifetime consumption. Specifically, we find that advance information about the long-run component of growth in the economy produces welfare benefits in the order of just 6% of lifetime consumption.

In order to correctly interpret this figure, we run the Lucas (1987) experiment in our economy and obtain welfare benefits of removing all uncertainty in the order of 65%.[15] As a result, the advance information that we identify in the cross section of industries represents less than 10% of the maximum attainable welfare benefits.

Epstein et al. (2014) point out that in the Bansal and Yaron (2004) model, most of the Lucas welfare benefits originate from full resolution of uncertainty, not from the removal of deterministic fluctuations. Our computations show that the early resolution of uncertainty in the cross section of industries is simultaneously valuable but limited, as it carries a strong market price of risk, but reveals future long-run consumption dynamics over a relatively short horizon.

We also look at the aforementioned model configurations under the special case of time-additive preferences, i.e., when $\psi = \frac{1}{\gamma} = 0.1$. Since in this case the representative agent does not care about the timing of resolution of uncertainty, advance information is not priced. As a result, the lead-lag expected return difference disappears, and our empirical findings take the form of an anomaly. In Appendix E, the reader can find explicit derivations of the LL premium in the context of simple lead-lag structures.

Link to our multifactor model. In order to investigate our model's ability to reproduce the cross-sectional pricing predictions found in the data, we construct a synthetic cross section of redundant dividend claims that differ in their exposure to fundamental shocks and in the timing of their exposure.

[15] This number is much smaller than that in Croce (2013), as our consumption process is calibrated according to post-1972 data, i.e., its volatility is moderate.

Table 12: Predictions for Quantities and Prices

Panel A: Benchmark Calibration

	δ^{12}	γ	ψ	12μ	$\sigma_c\sqrt{12}$	$V(x)/V(\Delta c)$	ρ	ϕ_x^{lead}	ϕ_x^{lag}	j_c	j_d
	0.99	10	1.50	1.80%	0.65%	0.57%	0.90	8.60	6.39	81	141
Data					0.65%	0.50%	0.83	8.60	6.39	81	141
s.e.					(0.02)		(0.04)	(3.86)	(4.71)		

Panel B: Main Moments

		EZ case ($\psi = 1.5$)			CRRA ($\psi = \gamma^{-1} = 0.1$)		
	DATA	Bench-mark	No lead ($j_c = j_d = 0$)	LRR only ($\phi_f^p = 0, \forall f$)	Bench-mark	No lead ($j_c = j_d = 0$)	LRR only ($\phi_f^p = 0, \forall f$)
$\mathbb{E}[r_d^{ex,lead} - r_d^{ex,lag}]$	4.04 (0.60)	3.09	1.66	3.48	0.04	0.03	0.00
$\mathbb{E}[r_d^{ex,lead}]$	9.00 (0.72)	7.64	7.84	7.37	0.28	0.28	0.00
$\mathbb{E}[r_d^{ex,lag}]$	4.96 (0.89)	4.56	6.19	3.89	0.24	0.24	0.00
$\sigma[r_d^{ex,lead}]$	16.79 (0.54)	26.83	26.24	26.50	17.08	9.08	16.46
$\sigma[r_d^{ex,lag}]$	18.85 (0.60)	22.03	25.00	19.20	15.74	17.60	15.34
$\mathbb{E}[r_f]$	0.94 (0.12)	2.24	2.22	2.24	19.01	19.01	19.01
$\mathbb{E}[r_c^{ex}]$	-	0.33	0.36	0.33	-0.30	-3.45	-0.30
$\sigma[r_c^{ex}]$	-	1.22	1.26	1.22	8.26	26.41	8.26
$\overline{U/C}$	-	3.99	3.76	3.99	1.34	1.31	1.34

Notes: Panel A summarizes the benchmark monthly calibration of the cash-flow dynamics described in equations (5)–(8). The entries for the data are obtained from formal estimation procedures applied to quarterly consumption and dividend data. The long-run risk volatility σ_x is selected to align the $V(x_t)/V(\Delta c)$ ratio in the model to the R^2 of our regressions in the data. For the leading portfolio, the annualized volatility of the dividend-specific shocks is set to 7%. For the lagged portfolio we use a figure twice as large, consistent with our estimation results. The exposures to short-run shocks are set as in appendix table D1. In panel B, we report key annualized moments in percentage terms. When we set $j_c = j_d = 0$, we remove all advance information about the long-run growth component in the economy. The column labeled 'LRR Only' features advance information about the long-run component, but it removes exposure of dividends to short-run consumption risk at all horizons ($\phi_f^p = 0, \forall f, p \in \{lead, lag\}$). The rightmost three columns refer to the case in which we adopt CRRA preferences ($\psi = \gamma^{-1}$). $\overline{U/C}$ denotes the average utility-consumption ratio. All standard errors are Newey-West adjusted.

Specifically, we let the dividends for stock i follow the dynamics specified in equation (8) with specific parameters $j_d^i, \phi_f^i, \ldots$. Since the effect of current and past short-run shocks on risk premiums is modest, we focus only on exposure to contemporaneous short-run shocks, i.e., we set $\phi_f^i = 0$ for all $f > 1$. For consistency, we re-estimate the system of equations (7)–(8) and report the new estimates in Table 13. We omit the long-run risk exposures ϕ_x^{lead} and ϕ_x^{lag}, because they remain unaffected.

Our simulated cross section of cash flows consists of (a) a leading dividend claim which depends on x_t; (b) a lagging asset that lags the leading claim by 141 months, i.e, it depends on x_{t-141}; and (c) fifteen additional lagging claims with specific lags j_d^i evenly spread out between 0 and 141 months. Thus, some assets lead aggregate consumption (those with a lagging period shorter than 81 months), whereas all other assets lag, as in the data.

Additionally, our synthetic assets differ in both their exposure to the long-run shock (ϕ_x^i) and their exposure to the short-run shock (ϕ_f^i). For the sake of consistency with the data, we also allow these cash flows to randomly differ in their idiosyncratic volatility (σ_d^i, $i = 1, .., 15$). This dimension is not crucial for our results.

For each synthetic asset, we uniformly draw a triplet $(\phi_x^i, \phi_f^i, \sigma_d^i)$ from our estimated intervals. For example, the interval for the ϕ_f^i values is consistent with the results in Table 13. Since we draw these parameters independently from j_d^i, we are able to simulate a cross section of returns in which heterogeneous exposure and heterogeneous timing of exposure to shocks are distinct phenomena.

We use many repetitions of small samples of simulated returns. In each sample, we construct the model-implied LL factor by computing the difference between leading and lagging claim returns, as in the data. We proxy the market factor (MKT) by focusing on the return of the claim to aggregate consumption. We then estimate the following linear factor models:

$$\begin{aligned} E[R_i^{ex}] &= \beta_{i,MKT}\lambda_{MKT} + v_i, \\ E[R_i^{ex}] &= \beta_{i,LL}\lambda_{LL} + v_i, \\ E[R_i^{ex}] &= \beta_{i,MKT}\lambda_{MKT} + \beta_{i,LL}\lambda_{LL} + v_i, \end{aligned} \tag{9}$$

where R_i^{ex} is mean excess return on a synthetic asset. For each sample, we compute the

Table 13: Short-Run Risk Exposure (Simplified)

ϕ_0^{lead}	ϕ_0^{lag}
6.58*	−6.12
(3.54)	(5.05)

Notes: This table presents estimated loadings of the leading and lagging dividends on the contemporaneous shock to the consumption growth, as specified in the system of equations (5)–(8). The estimation is restricted by imposing that $\phi_f^i = 0$, $\forall f > 1$, i.e., there is no anticipated information with respect to short-run consumption news. Numbers in parentheses are Newey-West adjusted standard errors.

mean squared error (MSE) between simulated returns and returns predicted by these three different factor-based models. We depict the implied distribution of MSEs across simulated samples in Figure 3 along with the point estimates obtained from our empirical investigation.

We highlight two important takeaways from this exercise. First, the cross section of our synthetic returns can be explained by a two-factor linear model, where the market factor picks up differences in exposure to risks, whereas the LL factor picks up heterogeneity in the timing of exposure. For this reason, the LL factor systematically improves the MSE by lowering its average and, more generally, by shifting more probability mass toward lower MSE values.

Second, under our benchmark calibration the model fit improvement

$$MFI = 1 - \sqrt{\text{MSE}(MKT + LL)/\text{MSE}(MKT)},$$

i.e., the relative improvement in MSE obtained by adding the LL factor, tends to be modest compared to its empirical counterpart. According to our simulations, the probability of observing our estimated MFI or a higher value is just 2%. The reason for this outcome is related to the fact that volatilities are calibrated to modest values under the benchmark calibration, and hence we do not have a sizeable heterogeneity across our relevant factors. When we refine our calibration and increase our volatility parameters so that the volatility of consumption growth is 2%, the improvement of fit associated with the LL factor becomes more sizeable and our empirical estimate corresponds to the 70^{th} percentile of our simulated distribution. We find this result reassuring: under a refined calibration consistent

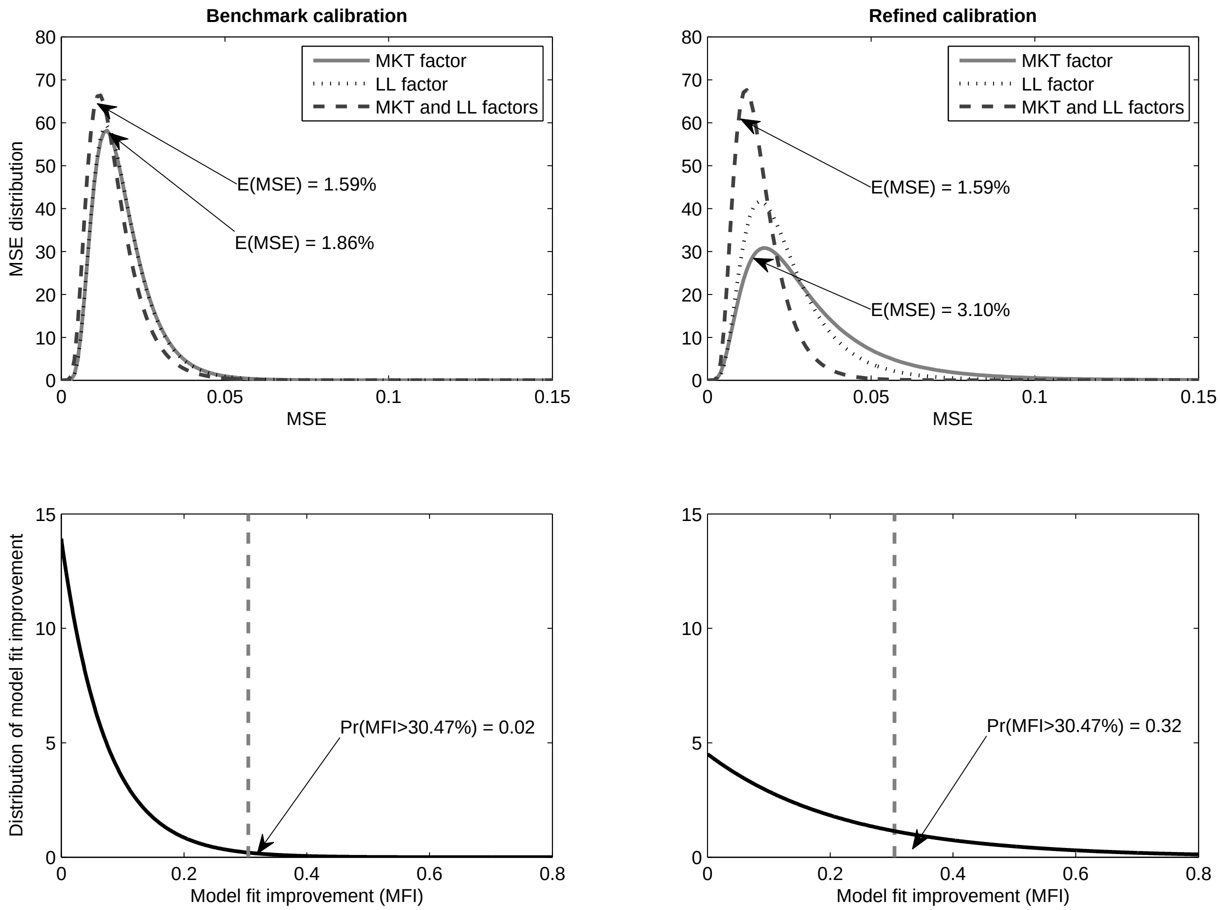


Fig. 3: Mean Squared Error (MSE) Distribution

This figure examines the goodness of fit of the factor models described in the system of equations (9). The entries from the model are obtained from repetitions of small samples. The entries from the data are obtained from our estimates derived from post-1972 quarterly data. In the model, we construct a cross section of synthetic assets whose cash flows lag to different extents the cash flow of the leading claim. Assets also randomly differ in their exposure to short- and long-run risk, as in the data. The LL factor is constructed as a spread in the returns of the most-leading and most-lagging portfolios. In the model, the market return is proxied by the consumption claim return. In the top panels, we depict the MSEs across simulated samples. In the bottom panels, we depict the empirical distribution of the model fit improvement (MFI) obtained by adding the LL factor to the MKT factor ($\text{MFI} = 1 - \sqrt{\text{MSE}(MKT + LL)/\text{MSE}(MKT)}$). The point estimate of MSE improvement in the data (using 30-industry portfolio returns) is represented by a vertical dashed line. The right panels are obtained using a refined calibration in which the total volatility of consumption growth is set to its 1929–2008 estimate of 2%.

with long-sample US consumption variance, our model performs well both qualitatively and quantitatively.

Further simulations results. Given our simulated cross section of cash-flows, we can now investigate the properties of our empirical approach based on cross-correlograms to pin

Table 14: LL Indicator for Simulated Cash Flows

Specification	Benchmark, no leads/lags	Benchmark	RW = 47 ML = 29	RW = 70, ML = 29
LL portfolio return	0.00	0.32***	2.00***	3.01***
s.e.	(0.03)	(0.07)	(0.08)	(0.11)
NW s.e.	(0.02)	(0.07)	(0.08)	(0.11)
Accuracy				
All leads	–	0.53	0.90	0.99
All lags	–	0.56	0.96	1.00
Leading Portfolio	–	0.75	0.98	1.00
Lagging Portfolio	–	0.64	0.90	0.99

Notes: This table provides average returns of the LL portfolio returns constructed by adopting our empirical LL indicator on our simulated cross section of cash flows. Monthly cash flows are simulated as described in section 4 and time-aggregated to the quarterly frequency. Under our benchmark procedure, for each asset we compute the ±4-quarter (maximum lead/lag, ML) cross-correlation between industry-level output growth and the output growth using 20-quarter rolling windows (RW). Second, we identify the lead or lag for which the maximum absolute cross-correlation is attained and assign it to the corresponding industry as its LL indicator. A positive (negative) LL indicator denotes an industry whose output growth leads (lags) GDP growth. The LL portfolio is a zero-investment strategy that is long in the top-3 leading assets and short in the top-3 lagging assets. The results from the first column refer to the case in which we apply our benchmark procedure to coincidental cash-flows ($j_d = j_c = 0$). In the rightmost two columns we alter RW and ML. We report in parentheses both simple and Newey and West (1987)-adjusted standard errors across small sample repetitions. The bottom portion of the table reports share of assets correctly identified as leading/lagging for all assets (All leads/lags), and for the assets that belong to the extreme Leading/Lagging portfolio. Each short sample contains 492 monthly observations. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

down the LL indicator. Our main results are reported in Table 14. The first column confirms that when the model cash flows are all coincidental ($j_c = j_d = 0$), our procedure produces no leading premium. Thus concerns about spurious results are mitigated.

When we instead have a proper lead/lag structure, our benchmark empirical procedure captures a positive and significant leading premium. Not surprisingly, the magnitude of the premium measured in the data is much smaller than the maximum spread implied by the model because the accuracy of the LL indicator in the data is rather imperfect and hence we are not identifying the most leading/lagging stocks with perfect accuracy. This result suggests that our empirical estimates for the premium may be considered rather conservative.

Most importantly, the next two column show that our LL indicator is consistent, meaning that it correctly sorts cash flows when we increase the length of our rolling window and we consider more leads and lags in the computation of our cross-correlograms. Increasing the maximum lead/lag in our cross-correlogram from 4 to 29 quarters of course also requires us to increase the length of our rolling window. When the rolling window length is set to 47 quarters, the accuracy of our LL indicator is enhanced and we recover most of the leading premium. With a 70-quarter window, the identification of leading and lagging assets is basically perfect.

5 Conclusion

In this study, we compute conditional leading/lagging indices for industry-level cash flows with respect to US GDP. We find that leading industries, i.e., industries whose cash flows contain information relevant for future aggregate growth, exhibit average returns that are approximately 4% higher than those of lagging industries.

This return difference remains sizeable and significant even after adjusting for a large number of other risk factors both in the time series and in the cross section of equity returns. After controlling for heterogenous exposure to risk, we find a pure annual timing premium of about 1.5%.

Our investigation implies at least two novel insights: (a) the cross section of industry returns can be significantly explained by heterogeneity in the timing of exposure to shocks; and (b) asset prices are sensitive to the timing of economic fluctuations.

We provide a theoretical foundation for our findings in the context of a rational equilibrium model in which agents have a preference for early resolution of uncertainty and hence price advance information about future cash flows. Our setting explains our empirical findings and suggests that advance information in the cross section of industry cash flows is valuable but limited, as it results in moderate welfare benefits.

Future work should extend our investigation by including other potentially valuable sources of anticipated information. This task could be accomplished by considering other classes of financial securities, such as domestic bonds, options, and international assets.

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Appendices

A Other Examples of our LL Cross Section

To provide further economic guidance about our measure, in Figure A1 we report our maximum correlation LL indicators for the consumer goods, manufacturing, and business equipment sectors. We focus on these large aggregates because their average lead-lag structure has been documented in the literature (see, among others, Greenwood and Hercowitz (1991) and Gomme et al. (2001)), and hence they represent a natural reference point for our methodology.

Consistent with prior studies, the unconditional average of the LL indicators in our sample suggests that the consumer goods sector leads national output by a little more than a month (a lead of 0.38 quarters), whereas manufacturing lags it slightly (a lag of around 0.6 quarters). Business equipment, i.e., investment goods, lag consumer goods by almost three quarters, as it takes time for firms to adjust their investment orders. Our LL indicators suggest that the lead-lag structure across these sectors experiences fluctuations that are pronounced over time but moderate in the cross section.

Specifically, during recession periods both the consumer goods sector and the business equipment sector tend to respond more promptly to shocks, as the former represents a stronger leading indicator, and the latter lags national output just by a few weeks. During booms, in contrast, both the consumer goods and the business equipment sectors lag the cycle by a longer period of time. The difference in the LL indicators of the two sectors, however, remains pretty stable, as it ranges from 2.13 quarters during recessions to 2.9 quarters during booms. In our main analysis with many industries, these cross sectional fluctuations become more relevant.

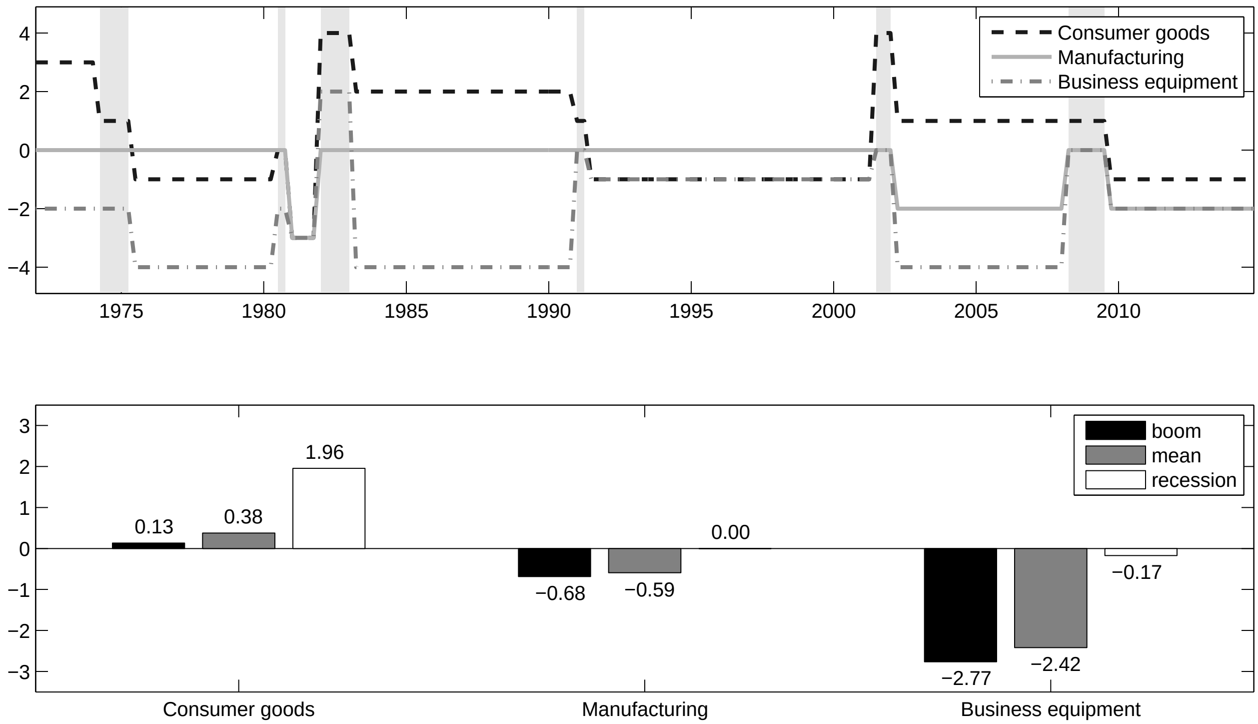

Fig. A1: Lead-Lag Indicator for Selected Industries

This figure depicts the lead-lag (LL) indicator for three major industries. The LL indicator is computed in two steps. First, for each industry, in each quarter we compute the ± 4-quarter cross-correlation between industry-level output growth and the domestic output growth using 20-quarter rolling windows. Second, we identify the lead or lag for which the maximum absolute cross-correlation is attained and assign it to the corresponding industry as its LL indicator. A positive (negative) LL indicator denotes an industry whose output growth leads (lags) GDP growth. Quarterly growth rates are adjusted for inflation and seasonality. In the top panel, grey bars denote NBER recession periods. In the bottom panel, we report for each industry the average of the LL indicator over our entire sample (denoted as "mean"), and its average value during booms and recessions.

B Data Sources and Additional Tables

In our empirical analysis, we use a cross section of monthly stock returns from the Center for Research in Security Prices (CRSP) and corresponding quarterly firm-level data from Standard & Poor's COMPUSTAT for the period January 1972 through December 2012. Prior to 1972, the quarterly data coverage is modest. All growth rates are in real terms and seasonally adjusted. We retrieve macroeconomic data series for GDP, consumption, and CPI from the website of the Federal Reserve Bank of St. Louis. Industry definitions based on SIC codes are taken from Kenneth French's website.

Table B1: LL Portfolio - Market Capitalization Share of Extreme Portfolios

	Returns on LL portfolio				
		Benchmark			
Minimum share,%	10	15	20	25	30
Average return	4.15^{*}	4.20^{**}	3.91^{**}	3.48^{**}	3.21^{**}
	(2.35)	(1.79)	(1.64)	(1.51)	(1.26)
CAPM α	4.85^{**}	4.96^{***}	4.54^{***}	4.04^{***}	3.58^{***}
	(2.35)	(1.89)	(1.72)	(1.54)	(1.31)
FF3 α	5.48^{**}	4.68^{**}	4.10^{**}	3.48^{**}	3.39^{**}
	(2.53)	(2.08)	(2.03)	(1.68)	(1.55)

Notes: This table provides average value-weighted returns of the LL portfolio, that is, a zero-dollar strategy long in Lead and short in Lag industries as defined in section 3. We depart from our benchmark portfolio construction by varying the minimal share of extreme portfolios in terms of market capitalization. In the benchmark specification, both the Lead and Lag portfolios represent at least 15% of the total market value in each quarter. Monthly return data start in 1972:01 and end in 2012:12. Industry definitions are from Kenneth French's website. The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table B2: Lead-Lag Portfolio Sorting: Cross-Industry LL Index

	Lead	Mid	Lag	LL
Panel A: 30 industries				
Average return	9.66***	5.84**	5.72**	3.95*
	(2.84)	(2.72)	(2.89)	(2.08)
CAPM α	3.21**	−0.90	−0.88	4.09*
	(1.57)	(0.60)	(1.30)	(2.20)
FF3 α	3.51**	−1.04	−1.37	4.87**
	(1.59)	(0.62)	(1.29)	(2.27)
Panel B: 38 industries	Lead	Mid	Lag	LL
Average return	8.40***	6.53**	4.64*	3.76**
	(2.41)	(2.88)	(2.61)	(1.90)
CAPM α	1.87*	−0.26	−1.79	3.65*
	(1.09)	(0.49)	(1.48)	(2.09)
FF3 α	1.96*	−0.20	−2.49	4.45**
	(1.13)	(0.50)	(1.49)	(2.13)
Panel C: 49 industries	Lead	Mid	Lag	LL
Average return	7.98***	6.86***	3.64	4.34**
	(2.67)	(2.67)	(2.86)	(1.71)
CAPM α	1.44	0.14	−2.89	4.33**
	(1.22)	(0.35)	(1.21)	(1.82)
FF3 α	1.40	0.05	−3.17	4.57**
	(1.47)	(0.34)	(1.30)	(2.17)

Notes: This table provides real annualized value-weighted returns of portfolios of firms sorted according to their cross-industry index of leads and lags (LL) as detailed in section 2. Our Lead (Lag) portfolio contains the top (bottom) 20% of our leading industries. These portfolios represent at least 15% of the total market value in each quarter. All other firms are assigned to the middle (Mid) portfolio. The LL portfolio reflects a zero-dollar strategy long in Lead and short in Lag. Return data are monthly over the sample 1972:01–2012:12. Industry definitions are from Kenneth French's website. CAPM α (FF3 α) denotes average excess returns unexplained by the CAPM (Fama-French three-factor model). The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table B3: LL Factor vs. Industry Momentum: Robustness

	Industry Momentum (Lag, Hold)		
	(1,1)	(6,6)	(12,12)
		30-industries LL factor	
MKT+indMOM	4.44**	4.14**	4.71**
	(1.75)	(1.69)	(1.92)
FF3+indMOM	4.09*	3.74**	4.17**
	(2.10)	(1.73)	(1.79)
		38-industries LL factor	
MKT+indMOM	4.09***	3.62**	3.27**
	(1.42)	(1.46)	(1.54)
FF3+indMOM	4.30**	4.20***	3.70**
	(1.70)	(1.52)	(1.64)
		49-industries LL factor	
MKT+indMOM	5.08**	4.51**	4.94**
	(2.09)	(1.86)	(2.09)
FF3+indMOM	4.50**	3.79**	4.07**
	(2.15)	(1.90)	(1.97)

Notes - This table reports the intercept α_{LL} of the regression of the LL factor constructed from the cross section of 30, 38 and 49 industries on the corresponding industry momentum factor with different formation (Lag) and holding (Hold) periods (1 period means 1 month). The industry momentum is constructed following the methodology of Moskowitz and Grinblatt (1999). We control for the market factor (MKT) and Fama and French 3 factors (FF3). Newey-West adjusted standard errors are reported in in parentheses. Monthly data start in 1972:01 and end in 2012:12. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table B4: LL Factor vs. Other Factors: Principal Component Analysis

α_{LL}	3.35**	3.19*	2.59*
	(1.68)	(1.68)	(1.45)
PC_1	0.09**	0.09**	0.09**
	(0.04)	(0.04)	(0.04)
PC_2	−0.14***	−0.14***	−0.14***
	(0.04)	(0.04)	(0.04)
PC_3	0.10	0.10	0.10
	(0.09)	(0.09)	(0.08)
PC_4		0.01	0.01
		(0.06)	(0.05)
PC_5		−0.05	−0.05
		(0.06)	(0.06)
PC_6			0.17**
			(0.08)
PC_7			0.23***
			(0.08)
Expl. Var	68.9%	83.8%	93.6%
Adj. R^2	0.11	0.11	0.16
# Obs.	492	492	492

Notes - This table reports the results from regressing the benchamrk LL factor constructed from the cross section of 30 industries on principal components extracted from Fama and French 5 factors, industry momentum (6,6) of Moskowitz and Grinblatt (1999), industry betting-against-beta, investment-minus-consumption, durability, quality-minus-junk and 30-industry momentum factors. *Expl. Var.* shows how much of the variation in the factors is explained by the selected principal components. Newey-West adjusted standard errors are reported in in parentheses. Monthly data start in 1972:01 and end in 2012:12. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table B5: LL Factor vs. Other Factors: Principal Component Analysis (II)

α_{LL}	3.42*	3.77*	3.47*
	(1.95)	(1.95)	(1.79)
PC_1	0.20***	0.20***	0.20***
	(0.03)	(0.03)	(0.03)
PC_2	0.02	0.02	0.02
	(0.05)	(0.05)	(0.05)
PC_3	0.03	0.03	0.03
	(0.10)	(0.10)	(0.10)
PC_4		−0.02	−0.02
		(0.06)	(0.06)
PC_5		0.10**	0.10**
		(0.05)	(0.05)
PC_6			0.08
			(0.08)
PC_7			0.14**
			(0.06)
Expl. Var	68.9%	83.8%	93.6%
Adj. R^2	0.13	0.14	0.15
# Obs.	492	492	492

Notes - This table reports the results from regressing the LL factor constructed from the cross section of 30 industries (using the cross-industry weighted index of leads and lags) on principal components extracted from Fama and French 5 factors, industry momentum (6,6) of Moskowitz and Grinblatt (1999), industry betting-against-beta, investment-minus-consumption, durability, quality-minus-junk and 30-industry momentum factors. *Expl. Var.* shows how much of the variation in the factors is explained by the selected principal components. Newey-West adjusted standard errors are reported in parentheses. Monthly data start in 1972:01 and end in 2012:12. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table B6: LL Factor during NBER Recessions and Booms

	α	β_{dummy}
30 industries	2.97*	8.42
	(1.80)	(6.70)
38 industries	3.81**	1.62
	(1.62)	(5.21)
49 industries	3.30*	8.83
	(1.89)	(6.47)

Notes: This table reports the results from regressing the LL factor on a recession dummy. The dummy takes on value of 1 during the NBER defined recession periods and 0 otherwise. Newey-West adjusted standard errors are reported in in parentheses. Monthly data start in 1972:01 and end in 2012:12.

Table B7: The Disconnect between LL and Other Factors (II)

Announcement Factor			Network Factor	
α_{LL}	4.28^{**}	4.56^{**}	α_{LL}	6.56^{***}
	(2.15)	(2.08)		(2.37)
MKT	-0.12	-0.12	MKT	-0.22^{***}
	(0.08)	(0.08)		(0.06)
SMB	0.04	0.04	SMB	-0.23^{***}
	(0.08)	(0.08)		(0.06)
HML	0.05	0.05	HML	-0.55^{***}
	(0.15)	(0.15)		(0.17)
SW_e	-0.01		TMB	0.11^{*}
	(0.02)			(0.06)
SW_n		-0.03		
		(0.02)		
Adj.R^2	0.02	0.03	Adj.R^2	0.41
# Obs.	492	492	# Obs.	110

Notes - The left portion of this table reports the results from regressing the LL factor constructed from the cross section of 30 industry portfolios on Fama and French 3 factors, market (MKT), size (SMB), and value (HML), together with earnings announcement value-weighted returns from Savor and Wilson (2016) for announcers (SW_e) and non-announcers (SW_n). The right portion of this table controls for the Top-Minus-Bottom (TMB) risk factor identified by Gofman et al. (2017) in production networks. Newey-West adjusted standard errors are reported in parentheses. Monthly data start in 1972:01 and end in 2010:12. The TMB factor is available starting from 2003:11.

Table B8: Lead-Lag Portfolio Sorting with Consumption

	Lead	Mid	Lag	LL
Average return	9.65^{***}	8.01^{***}	4.74	4.91^{*}
	(2.44)	(2.49)	(3.74)	(2.64)
CAPM α	2.54^{*}	0.27	-4.16^{*}	6.70^{**}
	(1.32)	(0.74)	(2.12)	(3.05)
FF3 α	2.12^{*}	-0.08	-3.27^{**}	5.39^{**}
	(1.23)	(0.67)	(1.58)	(2.21)
LL indicator	1.37	-0.19	-2.26	3.63
Turnover	0.04	0.07	0.05	0.07

Notes: This table provides real annualized value-weighted returns of portfolios of firms sorted according to their industry-level lead-lag (LL) indicator. We depart from our benchmark procedure for computing the LL indicator by (i) using consumption growth instead of GDP growth, and (ii) using Granger causality with a 40-quarter rolling window. A positive (negative) LL indicator denotes an industry whose output growth leads (lags) GDP growth. Our Lead (Lag) portfolio contains the top (bottom) 20% of our leading industries. These portfolios represent at least 15% of the total market value in each quarter. All other firms are assigned to the middle (Mid) portfolio. The LL indicator row refers to the average portfolio-level lead-lag indicators. Turnover measures the percentage of industries entering or exiting from a portfolio. Return data are monthly over the sample 1977:01–2012:12. Industry definitions are from Kenneth French's website. CAPM α (FF3 α) denotes average excess returns unexplained by the CAPM (Fama-French three-factor model). The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table B9: Prices of Risk and Pricing Kernel Loadings

Momentum factor

$$E[R_i^{ex}] = \beta_{MKT}\lambda_{MKT} + \beta_{SMB}\lambda_{SMB} + \beta_{HML}\lambda_{HML} + \beta_{MOM}\lambda_{MOM} + \beta_{LL}\lambda_{LL}$$

λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{MOM}	λ_{LL}
0.99***	-0.28	-0.07	0.31	0.89*
(0.23)	(0.20)	(0.23)	(0.73)	(0.49)

$$m_t = \overline{m} - b_{MKT}MKT_t - b_{SMB}SMB_t - b_{HML}HML_t - b_{MOM}MOM_t - b_{LL}LL_t$$

b_{MKT}	b_{SMB}	b_{HML}	b_{MOM}	b_{LL}
0.07***	-0.05**	0.01	0.01	0.10*
(0.01)	(0.02)	(0.04)	(0.05)	(0.06)

Durability factor

$$E[R_i^{ex}] = \beta_{MKT}\lambda_{MKT} + \beta_{SMB}\lambda_{SMB} + \beta_{HML}\lambda_{HML} + \beta_{DUR}\lambda_{DUR} + \beta_{LL}\lambda_{LL}$$

λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{DUR}	λ_{LL}
0.58***	-0.22	-0.07	0.04	0.65*
(0.19)	(0.23)	(0.23)	(0.21)	(0.39)

$$m_t = \overline{m} - b_{MKT}MKT_t - b_{SMB}SMB_t - b_{HML}HML_t - b_{DUR}DUR_t - b_{LL}LL_t$$

b_{MKT}	b_{SMB}	b_{HML}	b_{DUR}	b_{LL}
0.04***	-0.04	0.00	0.00	0.07*
(0.01)	(0.03)	(0.03)	(0.02)	(0.04)

Notes: This table presents factor risk premia and the exposures of the pricing kernel to the FF3 factors (MKT, SMB, HML), the Carhart (1997) momentum factor (MOM), the Gomes et al. (2009) durability factor (DUR) and our lead-lag factor (LL). We employ the generalized method of moments (GMM) to estimate the linear factor model stated in equations (2)–(3). Using a linear projection of the stochastic discount factor m on the factors ($m = \overline{m} - f'b$), we determine the pricing kernel coefficients as $b = E[ff']^{-1}\lambda$. Our sample consists of monthly returns for 49-industry portfolios from January 1972 through December 2012. The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

B.1 Further Robustness Checks

In this section, we carry out several robustness tests relevant for our empirical findings. We start by assessing alternative measures for our lead/lag indicator. We then consider a different way to correct for seasonality. Finally, we employ a sorting procedure based on Granger causality. All results are reported in Table B10.

Alternative Measures of Our LL Indicator. First, we consider the cross-correlation between quarterly GDP growth and industry cash flow growth within a larger 6-quarter window (as opposed to a 4-quarter window in our base case analysis). Second, instead of selecting the lead or lag for which the maximum absolute correlation is attained, we compute an average lead-lag weighted by the absolute values of the cross-correlation coefficients.[16] We find that the average return of our LL portfolio still cannot be explained by the FF3 model. These results suggest that our findings are not sensitive to the specific way in which we assign a lead-lag indicator to an industry.

X11 Method. Aggregate data are adjusted for seasonality by applying the X11 method, whereas our COMPUSTAT-based cash flow measures are seasonally-adjusted using dummy variables. Using the X11 method on industry-level cash flows does not alter our main results in a significant way.

Granger causality. In a variation of our benchmark approach we construct a lead-lag measure that employs the Granger causality to establish leads and lags between industry cash flow growth and GDP growth. In particular, we say that an industry is lagging GDP, if GDP growth Granger-causes the cash flow growth of this industry. In the opposite direction, an industry leads GDP if the industry cash flow growth Granger-causes GDP growth. In the absence of any causality, we assign zero to the lead-lag measure. When both time series Granger cause each other, we say that the lead-lag relation is undetermined and treat the respective industry cash flow as contemporaneous to GDP.

[16]In this case, the LL indicator is computed as $\sum_{i=-4}^{4} i \cdot \frac{|\rho_i|}{\sum_{i=-4}^{4} |\rho_i|}$, where $\rho^i = corr(\Delta GDP_t, \Delta CF_{t+i})$.

More specifically, we regress industry i's cash flow growth, Δg_t^i, on a constant, its past realizations, and past realizations of GDP growth, Δg^{GDP}, up to 4 lags each:

$$\Delta g_t^i = c + \sum_{j=1}^{4} \alpha_j \Delta g_{t-j}^i + \sum_{j=1}^{4} \gamma_j \Delta g_{t-j}^{GDP} + e_t^i. \tag{B.1}$$

We then test the null hypothesis $\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = 0$. If we reject the null (i.e., if at least one of the γ's is not equal to zero), we argue that Δg^{GDP} Granger causes Δg^i, meaning that industry i lags GDP. We identify the indicator value, that is, the corresponding lead, either by selecting the γ_j with highest significance (based on the respective t-statistic), or by computing the weighted average of all the γ_j coefficients using their t-statistics as weights (Granger Causality VW). For the Granger causality tests, we increase the rolling window to 40 quarters. We proceed in a similar way when looking at leads.[17] Our main results are robust to this alternative specification.

Alternative cash flow measures. A possible concern with respect to our analysis is that our results are driven by the use of the Acharya et al. (2014) cash flow measure. Table B11 and B12 confirm our findings on the leading premium also when we use dividends, operative income or investment-based measures of fundamental cash flows.

[17]In particular, for each industry we estimate the following equation:

$$\Delta g_t^{GDP} = c + \sum_{j=1}^{4} \alpha_j \Delta g_{t-j}^{GDP} + \sum_{j=1}^{4} \gamma_j \Delta g_{t-j}^i + e_t^i \tag{B.2}$$

If we fail to reject the null hypothesis, we conclude that cash flow growth of industry i Granger causes the GDP growth and consequently industry i leads GDP.

Table B10: Lead-Lag Portfolio: Granger Causality and Seasonal Adjustement

	±6 Lags		Average LL		x11 SAAR		Granger Causality		Granger Causality VW	
	LL	LL Strong	LL	LL Strong	LL	LL Strong	LL	LL Strong	LL	LL Strong
Average return	3.33*	3.76	2.67	3.16*	3.28*	3.99*	3.41*	4.84**	1.99	4.52**
	(2.00)	(2.43)	(1.64)	(1.71)	(1.86)	(2.06)	(2.05)	(1.94)	(1.51)	(2.03)
CAPM α	4.62**	5.07**	2.94*	3.25*	4.05**	4.91**	4.16**	5.06***	2.89*	5.25**
	(2.18)	(2.37)	(1.68)	(1.73)	(1.90)	(2.00)	(2.02)	(1.90)	(1.52)	(2.22)
FF3 α	3.03*	4.24*	2.95*	4.50***	3.97*	5.38**	4.07**	5.24***	3.62*	5.59*
	(1.57)	(2.30)	(1.58)	(1.56)	(2.27)	(2.36)	(1.94)	(1.95)	(1.89)	(2.86)
Turnover	0.07	0.06	0.08	0.06	0.12	0.10	0.14	0.11	0.07	0.05

Notes: This table provides average value-weighted excess returns unexplained by the Fama-French three-factor model (FF3) of the LL and LL Strong portfolios. The benchmark construction of the LL indicator is described in section 3. We depart from the benchmark procedure by either (a) seasonally adjusting the industry cash flows using the BEA x11 procedure instead of seasonal dummies or (b) using the Granger causality methodology to determine leads/lags instead of cross correlation; or (c) determining lead/lags using Granger causality, where lead and lags are weighted by respective t-statistics. LL refers to a zero-dollar strategy long in Lead and short in Lag. Return data are monthly over the sample 1972:01–2012:12. Industry definitions are from Kenneth French's website. The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table B11: Portfolio Sorting: Alternative Measures of Cash Flows

	Dividends		*OI*	
	LL	LL Strong	LL	LL Strong
Average return	3.28**	3.96**	5.25**	7.43***
	(1.51)	(2.01)	(2.09)	(2.08)
CAPM α	3.29**	4.59**	5.72***	7.74***
	(1.53)	(2.04)	(2.13)	(2.19)
FF3 α	4.15***	4.89**	6.44***	8.12***
	(1.56)	(2.06)	(2.16)	(2.29)

Notes: This table provides real annualized value-weighted returns of portfolios of firms sorted according to their industry-level lead-lag (LL) indicator. The formation of portfolios is similar to our benchmark specification with the only difference being the industry cash flow measure we use to construct the LL indicator. In this table, we report results for LL and LL Strong portfolios using dividends (*Dividends*) and operating income (*OI*) as our cash slow measures. Return data are monthly over the sample 1972:01–2012:12. Industry definitions are from Kenneth French's website. CAPM α (FF3 α) denotes average excess returns unexplained by the CAPM (Fama-French three-factor model). The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table B12: Portfolio Sorting: Alternative Measures of Cash Flows (II)

	CAPX		*PPEGT*	
	LL	LL Strong	LL	LL Strong
Average return	2.41*	4.19**	1.72	3.85**
	(1.41)	(1.73)	(1.64)	(1.78)
CAPM α	2.99**	4.24**	2.53	4.32**
	(1.50)	(1.85)	(1.80)	(1.93)
FF3 α	3.40**	4.32**	2.60	3.58**
	(1.56)	(1.92)	(1.81)	(1.70)

Notes: This table provides real annualized value-weighted returns of portfolios of firms sorted according to their industry-level lead-lag (LL) indicator. The formation of portfolios is similar to our benchmark specification with the only difference being the industry cash flow measure we use to construct the LL indicator. In this table, we report results for LL and LL Strong portfolios using capital expenditures (*CAPX*) and gross value of property, plant and equipment as our cash slow measures. Return data are monthly over the sample 1972:01–2012:12. Industry definitions are from Kenneth French's website. CAPM α (FF3 α) denotes average excess returns unexplained by the CAPM (Fama-French three-factor model). The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table B13: Lead-Lag Portfolio Sorting: Cash Flow Momentum

	Winners	Mid	Losers	W-L
Average return	8.60***	6.04**	6.41**	2.19
	(2.99)	(2.66)	(3.25)	(1.70)
CAPM α	1.8	−0.41	−0.81	2.62
	(1.22)	(0.56)	(1.30)	(1.79)
FF3 α	1.08	−0.41	−0.73	1.81
	(1.26)	(0.51)	(1.55)	(2.27)

Notes: This table provides real annualized value-weighted returns of portfolios of firms sorted according to their industry-level cash flow growth. First, in each quarter we compute the industry-level cash flow growth over past quarter. Our Winners (Losers) portfolio contains the top (bottom) 20% of industries with the highest (lowest) cash flow growth. These portfolios represent at least 15% of the total market value in each quarter. All other firms are assigned to the middle (Mid) portfolio. The W-L portfolio reflects a zero-dollar strategy long in Winners and short in Losers. Return data are monthly over the sample 1972:01–2012:12. Industry definitions are from Kenneth French's website. CAPM α (FF3 α) denotes average excess returns unexplained by the CAPM (Fama-French three-factor model). The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Cash flow growth momentum. Another concern regarding our interpretation of the results is that they are possibly just the reflection of past cash flow growth momentum, rather than a phenomenon related to advance information. In order to address this concern, we sort firms according to the past growth rate of their industry-level cash flow. We form a winners-minus-loosers investment strategy and look at the implied factor. We find no significant spread, meaning that our lead-lag sorting is not a reflection of fundamental momentum. Equivalently, our leading (lagging) firms are not systematically winners (losers).

Table B14: Static LL Portfolios Formation

	Average Return
Initial Sorting	1.00
	(1.28)
Unconditional LL	0.03
	(1.71)

Notes - This table reports the results his table provides real annualized value-weighted returns of portfolios of firms sorted according to their industry-level lead-lag (LL) indicator. The portfolios are formed at the beginning of the sample and rebalanced quarterly with respect to their value weights keeping the industry composition constant. The *Initial Sorting* row documents the average return of the LL portfolio (i) constructed at the beginning of the sample using our standard procedure; and (ii) never reformed. *Unconditional LL* is based on a full-sample computation of cross-correlations and an unconditional sorting. Newey-West adjusted standard errors are reported in parentheses. Monthly data start in 1972:01 and end in 2012:12. Industry definitions are from Kenneth French's website. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Formation frequency. Table B14 shows that our leading premium is mainly a conditional phenomenon. There is no premium when we either retain the sorting based on the initial estimate of the lead-lag indicator or when we estimate only one unconditional lead-lag indicator using the whole sample. On the other hand, Table B15 shows that our results do not hinge on high-frequency re-balancing and re-sorting. The leading premium can be captured even when we form our portfolios once a year.

Table B15: Lead-Lag Portfolio Sorting and Formation Frequency

Formation frequency	CAPM α	FF3 α
Quarterly	6.12^{***}	6.23^{**}
	(1.95)	(2.49)
Semiannual	5.33^{**}	5.22^{**}
	(2.13)	(2.13)
Annual	3.79^{*}	5.09^{***}
	(2.26)	(1.84)

Notes: This table provides real annualized value-weighted returns of portfolios of firms sorted according to their industry-level lead-lag (LL) indicator. The LL portfolio reflects a zero-dollar strategy long in Lead and short in Lag. In each portfolio, we identify the industries with the absolute value of correlation above the portfolio's median and group them in a subportfolio denoted as 'Strong'. This table shows the results of the LL Strong portfolio which is a zero-dollar trading strategy long in Lead Strong and short in Lag Strong. In our portfolio construction, we use 30 industries and three different frequencies of portfolio rebalancing: quarterly, semiannuallly and annually. Returns data are monthly over the sample 1972:01–2012:12. Industry definitions are from Kenneth French's website. CAPM α (FF3 α) denotes average excess returns unexplained by the CAPM (Fama-French three-factor model). The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

C Intuition based on no-arbitrage

Consider two stocks, denoted as *leading* and *lagging*. For the sake of simplicity, assume that they both pay dividends only once, n periods from now. From a time-0 perspective, the dividend of the leading firm, D_n^{lead}, is assumed to be unknown and random because the *leading* stock faces economic uncertainty. In order to abstract away from average growth, we assume $E_0[D_n^{lead}] = D_0^{lead}$. Consistent with our empirical analysis, we assume that the *leading* stock provides information about the future cash flow of the *lagging* firm. To make the intuition as crisp as possible, assume that $D_n^{lag} = D_0^{lead}$, that is, the future cash flow of the lagging stock is perfectly forecastable given the current cash flow of the leading firm.

Let $y_0(n)$ be the yield of a bond with maturity n and $v_0(n)$ be the dividend yield associated with the cash flow D_n^{lead}. Furthermore, assume for simplicity $D_0^{lead} = D_0^{lag} \equiv D_0$. By no arbitrage, the dividend yield for the lagging firm must be equal to $y_0(n)$, since its cash flow is known at time 0, so that $P_0^{lag} = D_0 e^{-y_0(n)n}$. In contrast, the leading firm must offer a yield of $v_0(n)$, i.e., $P_0^{lead} = D_0 e^{-v_0(n)n}$. This implies that the following holds:

$$\begin{aligned}\frac{P_0^{lag}}{D_0}\Big/\frac{P_0^{lead}}{D_0} &= \frac{pd_0^{lag}}{pd_0^{lead}} \\ &= e^{(v_0(n)-y_0(n))n} \\ &= \frac{E_0[D_n^{lead}]}{F_{0,n}},\end{aligned}$$

where $F_{0,n}$ is the future (or forward) price at time 0 for the dividend D_n^{lead} to be paid at time n, and pd_0^i is the price-dividend ratio of claim i at time 0. This implies

$$\frac{1}{n}\left(\log pd_0^{lag} - \log pd_0^{lead}\right) = v_0(n) - y_0(n),$$

i.e., the difference between the log valuation ratios of the lagging and the leading stock is equal to the forward equity premium (in the terminology of Binsbergen et al. (2012)) for a maturity of n periods.

If investors are adverse to dividend uncertainty, we have $F_{0,n} < E_0[D_n^{lead}]$, and lagging firms are more valuable than leading firms. Equivalently, an investment strategy long in the leading and short in the lagging stock should pay the forward equity premium on leading dividends.

This result is important for two reasons. First, the forward equity premium features no time-discounting, as it is determined by the difference between the expected dividend at time n and the certain payoff $F_{0,n}$ paid at time n, i.e., it can be regarded as the price of a static lottery. Hence this premium is a pure measure of the value of advance information on n-period ahead cash flows.

Second, the forward equity premium equals the difference between equity and bond yields of the *same* maturity. Thus to obtain a positive leading premium we need a model that produces a significant positive gap between the yield curve of zero-coupon equities and that of bonds over the horizon for which leading industry cash flows predict lagging industry cash flows.

It is important to highlight that the existence of a leading premium depends on the spread between the equity and the bond yield curve, not on the *slope* of the equity curve. In the main text, we adopt an equilibrium model that delivers an upward sloping aggregate equity yield curve for the sole sake of analytical tractability. Richer settings like those of Lettau and Wachter (2007), Lettau and Wachter (2011), Croce et al. (2014), and Ai et al. (2017), which are consistent with the empirical evidence in Binsbergen et al. (2012), Binsbergen et al. (2013), and Binsbergen and Koijen (2017), would produce similar insights about the nature of the leading premium.

Empirical support. The derivations described above suggest that lagging stocks should behave more like bonds, whereas leading stocks should behave more like uncertain aggregate equity. We provide further support to our analysis by estimating a quarterly VAR with three variables: aggregate bond yield, aggregate equity yield, and then the yield of either our lagging portfolio or our leading portfolio. The portfolio yields are computed in a standard way by using the cum- and ex-dividends return of our stocks. The bond yield is from the Fama-Bliss data set and is for a maturity of one year.

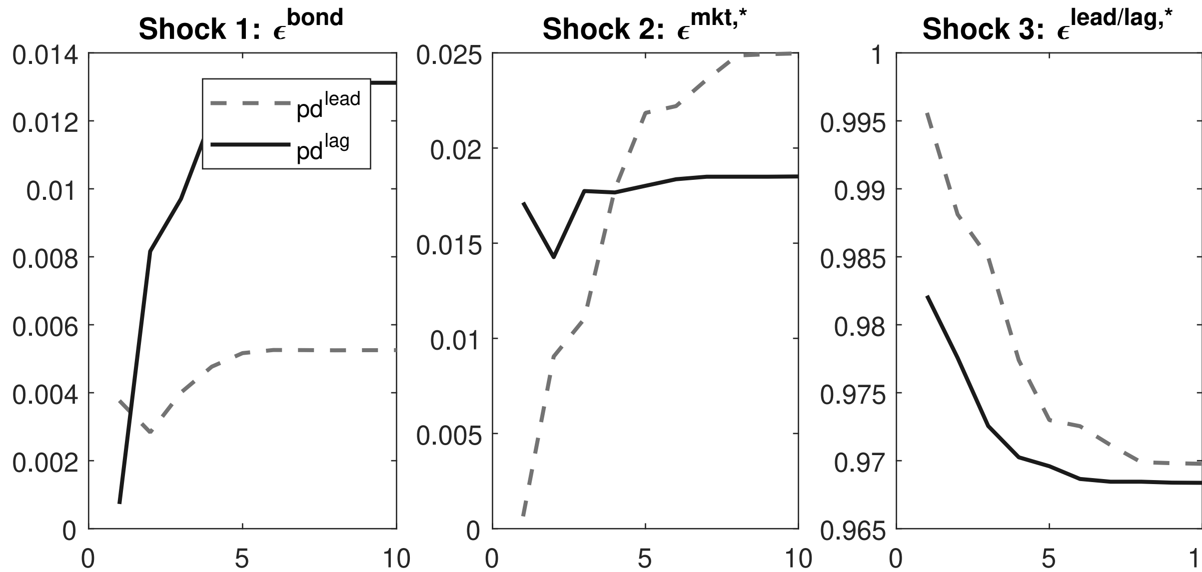

Fig. C2: Variance Decomposition of Leading/Lagging Portfolio Yields

This figure depicts the variance decomposition of the forecast error of the leading and lagging portfolio log yields estimated froma VAR(3). The variables in the model are: one-year bond yield; aggregate equity market log price-dividend ratio; and either leading or lagging log price-dividend ratio. The data is quarterly and spans the period 1972Q1:2012Q4.

After imposing a lower-triangular structure on the covariance matrix of the shocks, we can identify the role played by bond-specific and equity-specific shocks in determining the variance of our lagging and leading dividend yields. Since our results do not change if we rank the aggregate equity yield first and the bond yield second in our VAR, we do not need to take a stand on causality of bond and equity shocks for the purpose of our exercise.

In Figure C2, we show the variance decomposition for both our leading and lagging portfolios. Not surprisingly, given the persistence of dividend yields, the leading (lagging) yield-specific shock explains most of the variance of the leading (lagging) portfolio dividend yield (right panel). Most importantly, consistent with our intuition bond-specific shocks matter more than aggregate equity-specific shocks for our lagging portfolio (left panel). The opposite is true for our leading portfolio (middle panel).

Table D1: Information on Short-Run Consumption Shocks

Leading Portfolio								
ϕ_0^{lead}	6.58^{*}							
s.e.	(3.54)							
Lagging Portfolio: optimal $j_{lag} = 18$								
f	2	3	4	6	7	8	11	18
ϕ_f^{lag}	-11.33^{**}	-12.34^{***}	-8.69^{*}	6.94	9.29^{*}	11.97^{**}	11.56^{**}	12.37^{***}
s.e.	(4.61)	(4.69)	(4.78)	(4.71)	(4.76)	(4.74)	(4.60)	(4.54)

Notes: This table reports loadings of dividend claims on shocks to the consumption growth. Maximum lags $j_{2,lead}$ and $j_{2,lag}$ are chosen to maximize adjusted R-squared. Newey-West adjusted standard errors are reported in in parentheses. The quarterly data start in 1972:Q1 and end in 2012:Q4. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

D Cash Flow Dynamics

This section provides further details about the estimation of the cash flows described in equations (5)–(8). Specifically, the values for the time-horizons j_c, j_d, j_{lag} are selected in the range of ± 30 quarters for the long-run risk exposures and from 0 to 20 quarters for the short-run risk exposures. Our objective is to choose these integers in order to maximize the adjusted R^2. After determining the maximal lag for the short-run consumption shocks (j_{lag}), we re-estimate the model, restricting all statistically insignificant lagged exposures to be zero. Under our selected horizons, our regressions have an R^2 of 14% and 38% for leading and lagging dividend growth, respectively. We report the estimated loadings of leading and lagging portfolio cash flows on short-run shocks in table D1.

E Model Solution

In this section, we present derivations of the model solution in a general form. The consumption dynamics (5) can be written in the following generalized format:

$$\Delta c_{t+1} = \mu + A_{c|s} \cdot s_t + A_{c|\varepsilon^c} \varepsilon_{t+1}^c, \tag{E.1}$$

where $s_t = \begin{bmatrix} s_t^x \\ s_t^c \end{bmatrix}$ denotes the set of relevant state variables. The information set available to the investor at time t is $\mathbb{I}_t = \left\{x_{t-j_c}, \{\varepsilon_{t+1-i}^x, i = 1, .., j_c\}, \{\varepsilon_{t-f}^c, f = 1, .., f_c\}\right\}$.

The components of state vectors refer to anticipated information received in the past up until time t that has forecasting power for future consumption growth:

$$s_t^x = \underbrace{\begin{bmatrix} x_{t-j_c} \\ \varepsilon_{t-j_c+1}^x \\ \vdots \\ \varepsilon_t^x \end{bmatrix}}_{N_1 \times 1}, \quad s_t^c = \underbrace{\begin{bmatrix} \varepsilon_{t-f_c}^c \\ \varepsilon_{t-f_c+1}^c \\ \vdots \\ \varepsilon_t^c \end{bmatrix}}_{N_2 \times 1}, \quad N = N_1 + N_2. \tag{E.2}$$

The dynamics of the state vector can be represented as

$$\begin{aligned}
s_{t+1}^x &= \underbrace{\begin{bmatrix} \rho & 1 & 0 & \dots & 0 & 0 \\ 0 & 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & 0 & 1 \\ 0 & 0 & 0 & \dots & 0 & 0 \end{bmatrix}}_{\Lambda^x} s_t^x + \underbrace{\begin{bmatrix} 0 & 0 \\ 0 & 0 \\ \vdots & \vdots \\ 0 & 0 \\ 1 & 0 \end{bmatrix}}_{\Omega^x} \begin{bmatrix} \varepsilon_{t+1}^x \\ \varepsilon_{t+1}^c \end{bmatrix} \\
s_{t+1}^c &= \begin{bmatrix} \varepsilon_{t-f_c+1}^c \\ \varepsilon_{t-f_c}^c \\ \vdots \\ \varepsilon_t^c \\ \varepsilon_{t+1}^c \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & 1 & 0 & \dots & 0 & 0 \\ 0 & 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & 0 & 1 \\ 0 & 0 & 0 & \dots & 0 & 0 \end{bmatrix}}_{\Lambda^c} s_t^c + \underbrace{\begin{bmatrix} 0 & 0 \\ 0 & 0 \\ \vdots & \vdots \\ 0 & 0 \\ 0 & 1 \end{bmatrix}}_{\Omega^c} \begin{bmatrix} \varepsilon_{t+1}^x \\ \varepsilon_{t+1}^c \end{bmatrix} \\
s_{t+1} &= \begin{bmatrix} \Lambda^x & 0 \\ 0 & \Lambda^c \end{bmatrix} s_t + \begin{bmatrix} \Omega^x \\ \Omega^c \end{bmatrix} \begin{bmatrix} \varepsilon_{t+1}^x \\ \varepsilon_{t+1}^c \end{bmatrix}.
\end{aligned}$$

Consider a claim to aggregate consumption with price P_t^C at time t and let pc_t denote the log price-consumption ratio:

$$pc_t = \log\left(\frac{P_t^C}{C_t}\right). \tag{E.3}$$

The log-linearization of Campbell and Shiller (1988) implies

$$pc_t = \overline{pc} + A_{pc}s_t. \tag{E.4}$$

In our economy with recursive preferences, the pricing equation for consumption claim can be written as

$$\begin{aligned}
1 &= E\left[e^{\cdots - \frac{\theta}{\psi}\Delta c_{t+1} + \theta r_{t+1}^c} | \mathbb{I}_t\right] \\
&\approx E_t\left[e^{\cdots - \theta\left(1-\frac{1}{\psi}\right)A_{c|s}s_t + \theta\kappa_c A_{pc}s_{t+1} - \theta A_{pc}s_t}\right] \\
&\Downarrow \\
0 &= \theta\left(1-\tfrac{1}{\psi}\right)A_{c|s} + \theta\kappa_c A_{pc}\Lambda - \theta A_{pc} \\
&\Downarrow \\
A_{pc} &= \left(1-\tfrac{1}{\psi}\right)A_{c|s}\left(I-\kappa_c\Lambda\right)^{-1}.
\end{aligned}$$

Given this result, we can recover the log return on the consumption claim r_{t+1}^c, the risk-free rate r_t^f, and the stochastic discount factor m_{t+1}:

$$\begin{aligned}
r_{t+1}^c &= \overline{r^c} + \tfrac{1}{\psi}A_{c|s}s_t + \underbrace{\kappa_c\left(1-\frac{1}{\psi}\right)A_{c|s}\left(I-\kappa_c\Lambda\right)^{-1}\Omega}_{\eta_c}\,\varepsilon_{t+1}^s + A_{c|\varepsilon^c}\varepsilon_{t+1}^c \\
r_t^f &= \overline{r^f} + \tfrac{1}{\psi}A_{c|s}s_t \\
m_{t+1} &= \overline{m} - \tfrac{1}{\psi}A_{c|s}s_t - \underbrace{\kappa_c\left(\gamma-\frac{1}{\psi}\right)A_{c|s}\left(I-\kappa_c\Lambda\right)^{-1}\Omega}_{\eta_m}\,\varepsilon_{t+1}^s - \gamma A_{c|\varepsilon^c}\varepsilon_{t+1}^c.
\end{aligned} \tag{E.5}$$

Let $\eta \equiv A_{c|s}\left(I-\kappa_c\Lambda\right)^{-1}\Omega$, $\eta_c \equiv \kappa_c\left(1-\frac{1}{\psi}\right)\eta$ and $\eta_m \equiv \kappa_c\left(\gamma-\frac{1}{\psi}\right)\eta$ be 2-by-1 vectors of exposure coefficients to short- and long-run shocks. The system of equations (E.5) can be rewritten as follows:

$$\begin{aligned}
r^c_{t+1} &= \overline{r^c} + \tfrac{1}{\psi} A_{c|s} s_t + \Gamma_c v_{t+1} \\
\Gamma_c &= \left[\begin{array}{cccc} A_{c|\varepsilon^c} + \eta_{c,2} & \eta_{c,1} & 0 & 0 \end{array} \right] \\
m_{t+1} &= \overline{m} - \tfrac{1}{\psi} A_{c|s} s_t + \Gamma_m v_{t+1} \\
\Gamma_m &= \left[\begin{array}{cccc} -\gamma A_{c|\varepsilon^c} - \eta_{m,2} & -\eta_{m,1} & 0 & 0 \end{array} \right],
\end{aligned}$$

where $\eta_{c,k}$ and $\eta_{m,k}$ are the k-th components of the vectors η_c and η_m, respectively ($k = 1, 2$).

The expected excess return on the consumption claim reads as

$$\begin{aligned}
E_t[r^{ex,c}_{t+1}] &= -\mathrm{cov}(m_{t+1} - E_t[m_{t+1}], r^c_{t+1} - E_t[r^c_{t+1}]) - \tfrac{1}{2} V[r^c_{t+1} - E_t[r^c_{t+1}]] \\
&= -\Gamma_m \Sigma \Gamma_c' - \tfrac{1}{2} \Gamma_c \Sigma \Gamma_c'.
\end{aligned}$$

From the properties of the stochastic discount factor, it follows that

$$\begin{aligned}
E[r^f] &= -\log(\delta) + \tfrac{1}{\psi}\mu \tfrac{1-\theta}{\theta}(-\Gamma_m \Sigma \Gamma_c' - \tfrac{1}{2}\Gamma_c \Sigma \Gamma_c') - \tfrac{1}{2\theta} \Gamma_m \Sigma \Gamma_m', \\
\overline{m} &= \theta \log(\delta) - \tfrac{\theta}{\psi}\mu + (\theta - 1)\left(E[r^{ex,c}] + E[r^f] \right).
\end{aligned}$$

By evaluating the Euler equation for the consumption claim at $s_t = 0$, we obtain the equation for κ_c:

$$\kappa_c = e^{\overline{m} + \mu + \frac{1}{2} V[(\Gamma_m + \Gamma_c) v_{t+1}]}. \tag{E.6}$$

Similarly to Equation (E.1), the dividend growth dynamics in Equations (7) and (8) can be represented as

$$\Delta d_{t+1} = \mu + A_{d|s} \cdot s_t + A_{d|\varepsilon^c} \varepsilon^c_{t+1} + A_d \varepsilon^d_{t+1}, \tag{E.7}$$

which implies that the price-dividend ratio and the dividend returns have the following structure:

$$\begin{aligned}
pd_t &= \overline{pd} + A_{pd} s_t \\
r^d_{t+1} &= \overline{r^d} + \kappa_d pd_{t+1} - pd_t + \Delta d_{t+1},
\end{aligned}$$

where

$$A_{pd} = \left(A_{d|s} - \frac{1}{\psi} A_{c|s} \right) (I - \kappa_d \Lambda)^{-1}.$$

Consequently, in vector form the following holds:

$$\begin{aligned} r^d_{t+1} &= \overline{r^d} + \tfrac{1}{\psi} A_{c|s} s_t + \Gamma_d v_{t+1} \\ \Gamma_d &= \begin{bmatrix} A_{d|\varepsilon^c} + \eta_{d,2} & \eta_{d,1} & A_d & 0 \end{bmatrix} \\ \eta_d &= \kappa_d \left(A_{d|s} - \tfrac{1}{\psi} A_{c|s} \right) (I - \kappa_d \Lambda)^{-1} \Omega. \end{aligned}$$

The expected excess return on the dividend claim is

$$E_t[r^{ex,d}_{t+1}] = -\Gamma_m \Sigma \Gamma'_d - \frac{1}{2} \Gamma_d \Sigma \Gamma'_d.$$

By evaluating the Euler equation for the dividend claim at $s_t = 0$, we obtain the equation for κ_d:

$$\kappa_d = e^{\overline{m} + \mu + \frac{1}{2} V[(\Gamma_m + \Gamma_d) v_{t+1}]}.$$

E.1 Special Case I: Advance Information on Long-Run Risk Only

Consider a slightly modified version of the Bansal and Yaron (2004) economy in which consumption growth depends on a past value of the long run risk process x_{t-j_c}, i.e., the agent has advance information on the long-run component for j_c periods:

$$\Delta c_{t+1} = \mu + x_{t-j_c} + \varepsilon^c_{t+1} \tag{E.8}$$

$$x_{t+1} = \rho x_t + \varepsilon^x_{t+1}. \tag{E.9}$$

The investor's information set at time t consists of the realization x_{t-j_c} and shocks to long-run risk process up to date t $\left\{ \varepsilon^x_{t-j_c+1}, \dots, \varepsilon^x_t \right\}$. Consequently, we can rewrite the dynamics of the long-run component, using the state variables in the information set and the innovation ε^x_{t+1}, as

$$x_{t+1} = \rho^{j_c+1} x_{t-j_c} + \sum_{i=1}^{j_c} \rho^i \varepsilon^x_{t+1-i} + \varepsilon^x_{t+1}. \tag{E.10}$$

Following the standard solution approach, we consider a claim to aggregate consumption C, whose log price-to-cash flow ratio at time t is denoted by pc_t. One can show that pc_t is given as follows:

$$pc_t = \overline{pc} + A_x x_{j_c-1} + \sum_{i=1}^{j_c} A_i \varepsilon^x_{t-jc+i},$$

where

$$A_x = \frac{1}{1-1/\psi}\frac{1}{1-\kappa_c\rho}, \; A_i = \frac{(\kappa_c)^i}{1-1/\psi}\frac{1}{1-\kappa_c\rho}, i = 1, \ldots, j_c,$$

and the constant κ_c solves Equation (E.6).

Given this, we can obtain the log return on the consumption claim r^c_{t+1}, the risk-free rate r^f_t, and the stochastic discount factor m_{t+1} as follows:

$$\begin{aligned} r^c_{t+1} &= \overline{r^c} + \tfrac{1}{\psi}x_{t-j_c} + \varepsilon^c_{t+1} + \left(1-\tfrac{1}{\psi}\right)\tfrac{\kappa_c^{jc+1}}{1-\kappa_c\rho}\varepsilon^x_{t+1} \\ r^f_t &= \overline{r^f} + \tfrac{1}{\psi}x_{t-j_c} \\ m_{t+1} &= \overline{m} - \tfrac{1}{\psi}x_{t-j_c} - \gamma\varepsilon^c_{t+1} - \left(\gamma-\tfrac{1}{\psi}\right)\tfrac{\kappa_c^{jc+1}}{1-\kappa_c\rho}\varepsilon^x_{t+1}. \end{aligned} \tag{E.11}$$

Note that (E.11) is equivalent to the solution of the Bansal and Yaron (2004) economy when we set $j_c = 0$.

Up to a Jensen correction term the equity premium is:

$$\begin{aligned} E_t[r^{ex,c}_{t+1}] &\approx -\text{cov}(m_{t+1} - E_t[m_{t+1}], r^c_{t+1} - E_t[r^c_{t+1}]) \\ &= \gamma\sigma_c^2 + \tfrac{\kappa_c^{2jc+2}\left(1-\frac{1}{\psi}\right)\left(\gamma-\frac{1}{\psi}\right)}{(1-\kappa_c\rho)^2}\sigma_x^2. \end{aligned}$$

Since $\kappa_c < 1$, the contribution of the long-run risk component to the expected excess return on the consumption claim diminishes with the lag j_c, i.e., the longer in advance information is available, the lower the risk premium.

Let us now introduce a redundant claim with dividend growth defined by

$$\Delta d_{t+1} = \mu + \phi_x x_t + \varepsilon^d_{t+1}.$$

Relative to the consumption claim, this claim provides an investor with forward looking information about long-run risk. The log return and expected excess return (in levels) on the dividend claim can be expressed as

$$
\begin{aligned}
r_{t+1}^{d} &= \overline{r^{d}} + \frac{1}{\psi}x_{t-j_c} + \frac{\kappa_d\left(\phi_x - \frac{1}{\psi}\kappa_d^{j_c}\right)}{1-\kappa_d\rho}\varepsilon_{t+1}^{x} + \varepsilon_{t+1}^{d} \\
E_t[r_{t+1}^{ex,d}] &= -\mathrm{cov}(m_{t+1} - E_t[m_{t+1}], r_{t+1}^{d} - E_t[r_{t+1}^{d}]) \\
&= \frac{\kappa_c^{j_c+1}\kappa_d\left(\phi_x - \frac{1}{\psi}\kappa_d^{j_c}\right)\left(\gamma - \frac{1}{\psi}\right)}{(1-\kappa_c\rho)(1-\kappa_d\rho)}\sigma_x^2. \qquad \text{(E.12)}
\end{aligned}
$$

Assuming a preference for the early resolution of uncertainty ($\gamma > \frac{1}{\psi}$) and an elasticity of intertemporal substitution $\psi > 1$, the expected excess return increases with j_c, i.e., with the amount of time the dividend claim is actually leading the consumption claim.[18] With increasing j_c the dividend claim exhibits more and more information risk relative to the consumption claim, which in turn generates an increasing information premium as a component of the expected excess return.

E.2 Special Case II: Advance Information on Short-Run Risk Only

We now consider a different modification of the Bansal and Yaron (2004) setup in which a dividend claim depends on past realizations of shocks to consumption. Specifically, we assume that consumption growth depends on the long-run risk process as in the Bansal and Yaron (2004) setup. This is equivalent to setting j_c equal to 0. Next, we introduce a redundant asset whose cash flows depend on past realization of shocks to consumption. Thus, the cash flows in the economy can be represented as

$$
\begin{aligned}
\Delta c_{t+1} &= \mu + x_t + \varepsilon_{t+1}^{c} \qquad \text{(E.13)} \\
x_{t+1} &= \rho x_t + \varepsilon_{t+1}^{x} \qquad \text{(E.14)} \\
\Delta d_{t+1} &= \mu + \phi_x x_t + \phi_f \varepsilon_{t+1-f}^{c} + \varepsilon_{t+1}^{d}, \qquad \text{(E.15)}
\end{aligned}
$$

[18] To see this point, consider two different lag values, j_c and $j_c' : j_c' < j_c$. The fix point that determines the approximation constant for the dividends claim implies $k_d < k_d' < 1$. Simultaneously, $k_c' < k_c$, as more advance information reduces consumption risk.

where f is a lag of the consumption shock and ϕ_f stands for the loading of dividend growth on this shock.

Since there is no advance information about consumption, we obtain the following standard expressions for the log return on the consumption claim r^c_{t+1}, the risk-free rate r^f_t, and the stochastic discount factor m_{t+1}:

$$\begin{aligned}
r^c_{t+1} &= \overline{r^c} + \tfrac{1}{\psi}x_t + \varepsilon^c_{t+1} + \left(1 - \tfrac{1}{\psi}\right)\tfrac{\kappa_c}{1-\kappa_c\rho}\varepsilon^x_{t+1} \\
r^f_t &= \overline{r^f} + \tfrac{1}{\psi}x_t \\
m_{t+1} &= \overline{m} - \tfrac{1}{\psi}x_t - \gamma\varepsilon^c_{t+1} - \left(\gamma - \tfrac{1}{\psi}\right)\tfrac{\kappa_c}{1-\kappa_c\rho}\varepsilon^x_{t+1}.
\end{aligned} \tag{E.16}$$

Next, consider the dividend claim with cash flow dynamics specified in Equation (E.15). Conjecturing that the price-dividend ratio is affine in the state variables and using the Euler equation, we find that the return on this claim is given as follows:

$$r^d_{t+1} = \overline{r^d} + \frac{1}{\psi}x_t + \frac{\kappa_d\left(\phi_x - \frac{1}{\psi}\right)}{1-\kappa_d\rho}\varepsilon^x_{t+1} + \phi_f\kappa_d^{f+1}\epsilon^c_{t+1} + \varepsilon^d_{t+1}.$$

Apart from a Jensen correction term, the expected excess return on the dividend claim is

$$\begin{aligned}
E_t[r^{ex,d}_{t+1}] &= -\mathrm{cov}(m_{t+1} - E_t[m_{t+1}], r^d_{t+1} - E_t[r^d_{t+1}]) \\
&= \gamma\phi_f\kappa_d^{f+1}\sigma_c^2 + \frac{\kappa_c\kappa_d\left(\phi_x - \frac{1}{\psi}\right)\left(\gamma - \frac{1}{\psi}\right)}{(1-\kappa_c\rho)(1-\kappa_d\rho)}\sigma_x^2,
\end{aligned} \tag{E.17}$$

implying that advance information on the short-run shock reduces the required risk premium, although to a much more modest extent, because the market price of risk on short-run shocks is not as large as that on long-run news shocks (as one can see from a comparison of the expressions (E.12) and (E.17)).