The Leading Premium

M. Max Croce   Tatyana Marchuk   Christian Schlag*

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. The difference in the returns of leading and lagging firms is priced in the cross section of equity returns, even after we control for a large number of risk factors. 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.
First draft: Sept. 16, 2015. *This draft*: December 11, 2017.

*Croce is affiliated with the Kenan-Flagler Business School, University of North Carolina at Chapel Hill, and CEPR. Marchuk is affiliated with the Finance Department of BI Norwegian Business School. Schlag is affiliated with the Finance Department and Research Center SAFE at Goethe University Frankfurt . We thank E. Farhi, C. Julliard, and M. Yogo, and S. van Nieuwerburgh for early feedback. We are very grateful to our discussants Thomas Q. Pedersen and Jun Li. We also thank the seminar participants at the CEPR meetings, WFA Meetings, SED Mettings, Econometric Society Meetings, SGF Meeting, Macro-Finance Society Meeting, Kenan-Flagler Business School, Tilburg University (Finance), Maastricht University (Finance), Hong Kong University of Science and Technology, Toronto University, Carlson School of Management and SAFE.

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. This figure remains as significant as both the equity and the value premium even after controlling for a large number of related factors in time-series tests.

In order to perform also cross-sectional tests, 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. A formal GMM estimation of a linear pricing model with both the LL and the Fama and French (1993) three factors (FF3 hereafter) shows that LL is priced in our cross section of industry portfolio returns, suggesting that we are focusing on a novel firm characteristic.

Furthermore, the LL factor has a significant loading in the model-implied stochastic discount factor, implying that asset prices are sensitive to the timing of economic fluctuations. Consistent with this intuition, 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.[2] In each quarter, we

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

focus on a four-quarter window of leads and lags. After identifying the highest correlation in absolute value within this window, we assign the corresponding lead/lag indicator (ranging from -4 to $+4$) 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. We speculate that this may depend on the origin of the underlying economic shock affecting firms. As an example, the firms leading during an IT boom do not necessarily lead during a financial crisis. In Appendix D, 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 production growth shocks. Possible microfoundations of our diffusion are provided in Caplin and Leahy (1993, 1994).

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 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 after adjusting, for example, for the FF3 factors. The industries with the highest exposure to our LL factor are also the ones whose operating income strongly leads national output.

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, and the q-Factors (Hou et al. 2015a, b).

We use a stylized example to build up intuition and show via a simple no arbitrage argument 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 leading premium. For the sake of analytical tractability, we abstract away from investment decisions (Albuquerque and Miao 2014) and consider the endowment economy of Bansal and Yaron (2004), in which consumption growth is subject to persistent news shocks, which are directly priced by Epstein and Zin (1989) (EZ) preferences.

In the spirit of Bansal et al. (2005), we use this model to price a cross section of cash flows that differ from each other in their lead-lag structure, with the goal of explaining our leading premium. Specifically, we project consumption growth in the US on the Jurado et al. (2015) factors to identify the aggregate long-run growth component and disentangle it from short-run growth shocks. We then compute the cash flows from investing in our leading and lagging portfolios, respectively. In a second step, we project the cash-flow growth rates on leads and lags of the components of consumption growth.

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 also accounts for heterogeneity in the exposure of cash flows to fundamental consumption growth shocks.

As mentioned above, prior manuscripts have already documented that heterogeneous exposure to contemporaneous news shocks can explain the value premium (see, among others, Bansal et al. 2005). We differ from prior studies by showing that *heterogeneous timing* of exposure to news shocks explains the leading premium. Consistent with the data, when calibrating our cash-flow processes we control for heterogeneous exposure to fundamental shocks in order to obtain the most proper and conservative prediction for the model-implied leading premium.

In the data, we find that the cash flows of the leading portfolio provide information about the long-run consumption growth component 27 quarters ahead. The time gap increases to 47 quarters with respect to the lagging portfolio, implying that this latter portfolio benefits substantially from early resolution of uncertainty. Under a standard calibration of the model consistent with our data, the implied leading premium is 3.10%, a figure very close to our estimate and almost completely driven by the long-run shocks in our model. The short-run shocks play a role only when we create a synthetic cross section of stocks that differ in both their lead-lag structure and their exposure to short-run risk, as in the data. In this case, our equilibrium cross section of returns has a two-factor representation, and the implied synthetic LL factor is priced in addition to the market factor, consistent with our empirical evidence.

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%.[3] 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.

Patton and Verado (2012) and Savor and Wilson (2016) document the existence of higher risk for firms that release advance information by announcing their earnings. Ai and Bansal (2015) provide a theoretical foundation of the announcement premiums, including those in Savor and Wilson (2013). Kadan and Manela (2016) estimate the value of information using options. Our main goal is to empirically quantify the relevance of heterogeneity in the timing of exposure of cash flows to aggregate shocks for the cross section of industry returns. Our results are significant beyond announcement events.

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. Working with the cross section of bond and equity returns, 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. We differ from their work in our focus on industries, our empirical and theoretical characterization of the leading premium, and the assessment of the welfare benefits stemming from advance information about future growth.

Based on the observation that some components of aggregate consumption are more cyclical than others, Gomes et al. (2009) show that durable good producers have cash flows both more volatile and more highly correlated with aggregate consumption than those of firms producing nondurables and services. Furthermore, output durability is a priced factor in the cross section of equity returns. We differ from this study in our attention toward heterogeneity in the timing of exposure to fundamental shocks.

Fama and French (1997) find that the FF3 model exhibits only modest performance in explaining the cross section of industry returns. Our LL factor significantly improves our ability to explain industry returns above and beyond what is documented in other studies.

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

[3] 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.

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. In the context of a rational equilibrium model in which anticipated news is priced, there exists a link between the timing of cash-flow exposure and expected returns. Our endogenous cross section of *returns* features no lead-lag structure, that is, all returns move simultaneously, but with different endogenous sensitivities.

As we show by means of a stylized example in section 3, the existence of a leading premium does not depend on the slope of the equity yield curve, but just on the spread between the the equity and the risk-free bond yield curve. Richer settings like those suggested by Lettau and Wachter (2007, 2011), Croce et al. (2014), and Ai et al. (2017), 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 present the setup and results of our empirical analysis. In Section 3 we describe our model. Section 4 concludes.

2 Empirical Investigation

Data sources and the LL indicator. In our empirical analysis, we use monthly stock returns from CRSP as well as the corresponding quarterly data from COMPUSTAT from 1972:01–2012:12. 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. As in Acharya et al. (2014), we compute industry-level output by aggregating firms' operating income before depreciation and net of interest expenses, income taxes, and dividends. 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).

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. We then identify the lead-lag for which the maximum absolute cross-correlation is attained and assign it to the corresponding industry. This procedure generates a panel of 30 industry-level lead-lag (LL) indicators spanning 41 years.

To provide economic guidance about our measure, in Figure 1 we report our 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.

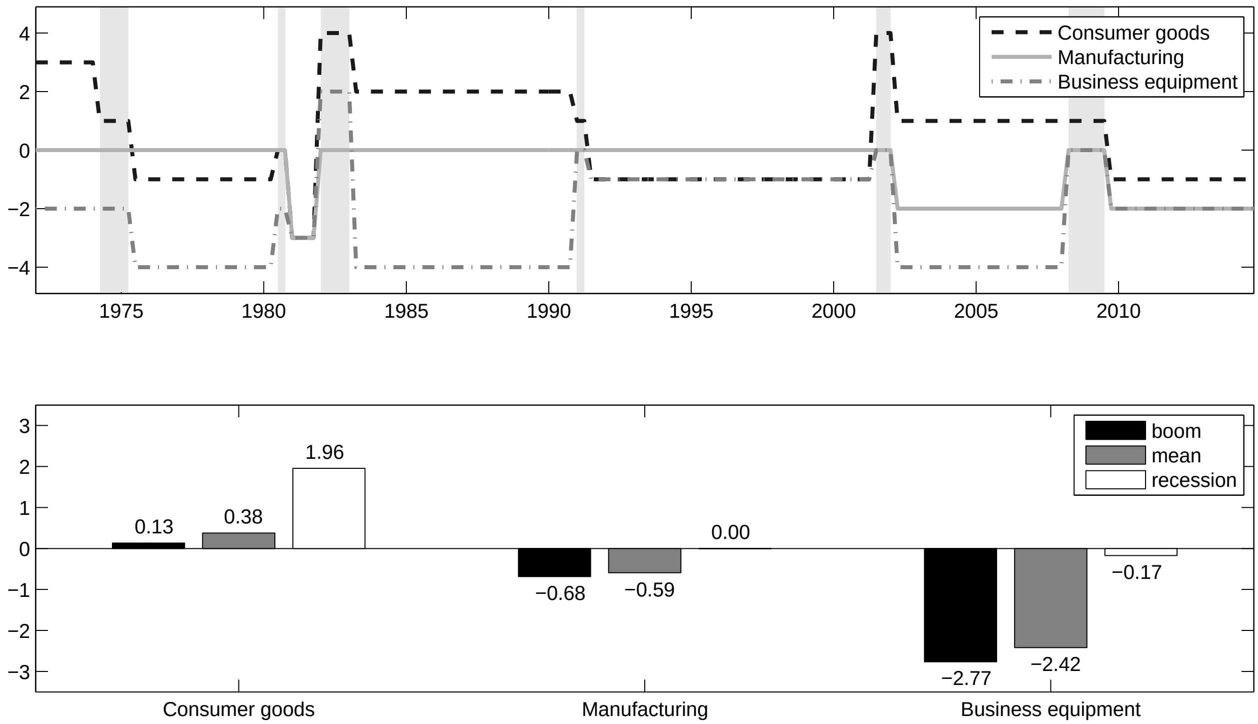

Fig. 1: Lead-Lag Indicator for Selected Industries

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.

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 what follows, we document that these cross sectional fluctuations become more relevant when we work with 30 industries.

2.1 Time-Series Analysis

Portfolio sorting and the LL factor. Each quarter, we sort our 30 industries according to their 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.

As shown in Table 1, the industries in our lag portfolio go through economic fluctuations with an average delay of 5.95 quarters compared to the leading industries. The average quarterly turnover is comparable across the two extreme portfolios and ranges from 33% to 42%.[4] Since we work with 30 industries, our cross section is not as fine as in other studies; hence, these numbers should be interpreted as significant, but not excessive.

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 A, we show that these results continue to hold also when we consider different quantiles for the formation of the lead and lag portfolios (see Table A1).

Second, the return of the LL factor is concentrated in the leading portfolio against all the others. Our theoretical investigation shows that this empirical fact is an equilibrium outcome when aggregate consumption news is priced. The reason for this is that the leading premium applies mostly to cash flows that strictly lead aggregate output, i.e., those that have a positive LL indicator.

Third, 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

[4]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 of the portfolio considered. Expressing turnover in market value terms prevents our measure from being driven by many small industries frequently moving across portfolios. At the industry level, the average frequency of migrating across portfolios is 28%, with a cross sectional standard deviation of 7.5%.

Table 1: Lead-Lag Portfolio Sorting

	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)
LL indicator	2.85	−0.23	−3.11	5.95	–
Turnover	0.39	0.22	0.42	0.35	0.45

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 $\pm$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. 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.

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.

Granularity. We explore the role of granularity and report key results on the leading premium in Table 2. 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 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.

Table 2: 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	0.30	0.48	0.31	0.43

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.

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 3.

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 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 firms that 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.

Table 3: 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.

LL's disconnect from other factors. We formalize further the disconnect between our leading premium and the FF3 factors through standard tests. 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 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).

We show our estimates for the following regression:

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

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.[5] Untabulated results confirm that these conclusions can be obtained also when considering more granular cross sections with either 38 or 49 industries.

We deepen our analysis by exploring the connection between the leading factor, the q-

[5]The negative beta assigned to the IMC factor is fully consistent with Figure 1, as industries producing investment goods tend to lag the cycle.

Table 4: The Disconnect between LL and Other Factors

	(1)	(2)	(3)	(4)	(5)	(6)
α_{LL}	4.96***	4.68**	4.61**	4.55**	4.57**	4.22**
	(1.89)	(2.08)	(2.00)	(1.90)	(2.09)	(1.94)
MKT	−0.13*	−0.13	−0.07	−0.12*	−0.12	−0.11
	(0.08)	(0.09)	(0.08)	(0.07)	(0.09)	(0.07)
SMB		0.04	0.13	0.05	0.03	0.07
		(0.08)	(0.10)	(0.07)	(0.08)	(0.09)
HML		0.04	−0.06	0.05	0.05	−0.06
		(0.16)	(0.13)	(0.13)	(0.15)	(0.14)
IMC			−0.26***			
			(0.09)			
DUR				−0.03		
				(0.08)		
iMOM					0.07*	
					(0.04)	
iBAB						0.28***
						(0.10)
Adj. R^2	0.03	0.03	0.08	0.03	0.04	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.

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 5, 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 A2 in the appendix). Hence our factor is distinct from that in Lettau et al. (2014). In Table A6, 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).

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 employment 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.

Table 5: 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***
	(2.23)		(2.40)		(1.91)	(1.92)	(2.35)
MKT	−0.08	MKT	−0.11*	MKT		−0.14*	−0.10
	(0.07)		(0.06)			(0.08)	(0.08)
SMB	−0.06	ME	−0.04	MOM	0.12	0.10	0.11
	(0.10)		(0.07)		(0.10)	(0.09)	(0.08)
HML	−0.10	I/A	0.03	SMB			−0.14*
	(0.18)		(0.18)				(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.

We report our findings in Table 6 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 LL factor 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).

2.2 Further Robustness Checks

In this section, we carry out several robustness tests relevant for our empirical findings. We start by proposing alternative measures for our lead/lag indicator. We then consider an alternative way to correct for seasonality. Finally, we consider a sorting procedure based on Granger causality. All results are reported in Table 7.

Table 6: 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:

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

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

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

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.

Alternative Measures of Our LL Indicator. We perform several robustness checks with respect to the computation of the 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

Table 7: Robustness Checks

	±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
CAPM α	4.62**	5.07**	2.94*	3.25*	4.05**	4.91**	3.20*	4.97**	2.89*	5.25**
	(2.13)	(2.41)	(1.68)	(1.73)	(1.90)	(2.00)	(1.66)	(2.52)	(1.52)	(2.22)
FF3 α	3.03*	4.24*	2.95*	4.50***	3.97*	5.38**	3.56*	4.8	3.62*	5.59*
	(1.76)	(2.43)	(1.58)	(1.56)	(2.27)	(2.36)	(2.02)	(3.17)	(1.89)	(2.86)
Turnover	0.19	0.28	0.21	0.27	0.32	0.43	0.18	0.27	0.17	0.25

Notes: This table is based on real annualized value-weighted returns of portfolios of firms sorted according to their industry-level lead-lag (LL) indicator. Both the LL factor and the LL Strong factor are computed as in table 1. 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. Results from the benchmark formation of the portfolios are reported in table 1. Here we depart from the benchmark procedure by (a) taking the maximum cross-correlation over a ±6-quarter horizon; (b) taking an average of the leads/lags over a ±4-quarter horizon weighted by their cross-correlations in absolute values; (c) seasonally adjusting the industry cash flows using the BEA X11 procedure instead of seasonal dummies; (d) using the Granger causality methodology to determine leads/lags instead of cross correlations; (e) determining lead/lags using Granger causality where lead and lags are weighted by their respective t-statistics.

an average lead-lag weighted by the absolute values of the cross-correlation coefficients.[6] 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.

More specifically, we regress industry i's cash-flows growth, Δg_t^i, on a constant, its past realization up to 4 lags, as well as past realizations of GDP growth, Δg^{GDP}:

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

We then test the hypothesis $H_0 : \gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = 0$. If we fail to reject H_0, 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 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.[7] Our main results are robust to this alternative specification. Furthermore, in Appendix A we show that our results continue to hold also when we consider

[6] 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 $\rho^i = corr(\Delta GDP_t, \Delta CF_{t+i})$.

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

$$\Delta g_t^{GDP} = c + \sum_{j=1}^{4} \alpha_j \Delta g_{t-j}^{GDP} + \sum_{j=1}^{4} \gamma_j \Delta g_{t-j}^i + e_t^i \tag{3}$$

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.

aggregate consumption growth as opposed to GDP growth (see Table A3).

2.3 Cross Sectional Tests

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

$$R_{i,t}^{ex} = a_i + \beta_i \cdot F_t + u_{i,t} \quad (4)$$

$$E[R_{i,t}^{ex}] = \beta_i \lambda + v_i, \quad (5)$$

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. Efficient standard errors are corrected for autocorrelation and heteroskedasticity following Newey and West (1987).[8] Our goal is to test whether our LL risk factor is priced in the cross section of equity returns.

We first run an unconditional analysis with respect to the role of LL in the pricing of industries. The purpose of this first step is to show that the LL-beta of an industry is closely related to the value obtained for the LL indicator for this industry. This justifies that in the ensuing conditional analysis individual stocks are sorted with respect to their conditional betas for the LL factor.

Pricing industries. We start our analysis using portfolios based on 30 industries as test assets. Table 8 provides some guidance on our estimated industry-level exposure to the LL factor. Specifically, we focus on the three industries that most frequently enter the leading and the lagging portfolios. For each industry, we show its returns loading on the LL factor (β_{LL}), its average market share, and descriptive statistics concerning its LL indicator.

First of all, we note that the exposure to the LL risk factor of the most frequently leading firms are all positive, whereas the opposite is true for the three industries most frequently included in the lagging portfolio. We consider this result as an important consistency check.

Second, in interpreting the numerical values of these exposures one has to keep in mind that even the three most frequently leading or lagging industries are not always included in the respective portfolio, implying that the unconditional measures that we report tend to have moderate cross-sectional variation. As an example, in the 2007 recession Finance was a leading industry, but historically it lagged GDP slightly.

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. In each panel, the top portion refers to our setting where portfolios ar formed from 30 industries (30-industry

[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.

Table 8: Industry Exposures to the Lead-Lag Factor

Top 3 industries				
	β_{LL}	Market share,%	LL Indicator	
			Mean	Median
Health	0.23	10.39	0.02	1.00
Tobacco products	0.23	0.88	0.31	1.00
Consumer goods	0.18	4.88	0.20	0.00
Bottom 3 industries				
	β_{LL}	Market share,%	LL Indicator	
			Mean	Median
Business equipment	-0.26	11.64	-0.97	-1.00
Finance	-0.00	2.56	-0.55	-1.00
Telecommunication	-0.08	5.76	-0.29	-1.00

Notes: This table provides a summary of the first stage of our GMM estimation of the linear factor model detailed in equations (4) and (5). The top (bottom) panel lists the top three industries most frequently included in our leading (lagging) portfolio. β_{LL} represents the exposure of industry returns to the LL risk factor. Market share is the average market value of the industry of interest divided by total market capitalization over our sample (1972:01–2012:12). LL Indicator denotes the lead (when positive) or the lag (when negative) of industry cash-flow growth with respect to U.S. output growth. The indicator is computed in two steps. First, each quarter we compute the cross-correlation between industry-level output growth and domestic output growth for leads and lags of up to four quarters each using a rolling window of 20 quarters. Second, we identify the lead or lag for which the maximum absolute cross-correlation is attained and assign it to the corresponding industry. A positive (negative) LL indicator denotes an industry whose output growth leads (lags) GDP growth.

portfolios). As in Cochrane (2005), we represent the discount factor as $m_t = \overline{m} - bf_t$, so that

$$b = E(f_t f_t')^{-1}\lambda, \tag{6}$$

where $f_t = [MKT_t,\ SMB_t,\ HML_t,\ LL_t]$ is the the vector of factors. We find that both the factor risk premium λ_{LL} and the pricing kernel loading b_{LL} are statistically significant at the 10% level. Hence, these tests confirm that our LL factor is both relevant and required when it comes to pricing the cross section of industry excess returns. These results are robust and hold also when working with 38- and 49-industry portfolios.[9] In Appendix A, 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 (see Table A4).

Cross-sectional fit at the industry-level. In Figure 2, we depict the link between the average excess returns predicted by our four-factor model (x-axis) and their realized

[9] 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 9: Prices of Risk and Pricing Kernel Loadings

$E[R_i^{ex}] = \beta_{MKT}\lambda_{MKT} + \beta_{SMB}\lambda_{SMB} + \beta_{HML}\lambda_{HML} + \beta_{LL}\lambda_{LL}$			
λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{LL}
30 industries			
0.56***	-0.14	-0.03	0.71*
(0.21)	(0.25)	(0.23)	(0.39)
38 industries			
0.56***	-0.20	0.04	0.61*
(0.20)	(0.20)	(0.26)	(0.32)
49 industries			
0.58***	-0.21	-0.09	0.67*
(0.20)	(0.23)	(0.25)	(0.41)
$m_t = \overline{m} - b_{MKT}MKT_t - b_{SMB}SMB_t - b_{HML}HML_t - b_{LL}LL_t$			
b_{MKT}	b_{SMB}	b_{HML}	b_{LL}
30 industries			
0.04***	-0.03	0.00	0.07**
(0.01)	(0.03)	(0.03)	(0.04)
38 industries			
0.04***	-0.03	0.02	0.07**
(0.01)	(0.02)	(0.03)	(0.03)
49 industries			
0.04***	-0.05*	-0.01	0.08**
(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 (4)–(5). 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 30-, 38- and 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.

counterparts (y-axis) for the 30-industry portfolios. We obtain similar results also when working with 38- and 49-industry portfolios (see Table A5 in the appendix).

The top (bottom) left panel shows the results for the CAPM (FF3) model. The corresponding graphs on the right show how the results change when we add the LL factor to the base models shown on the left. Given this representation, improvements in the model fit imply combinations of predicted and realized average excess returns located closer to the 45-degree line. A visual inspection of our graphs reveals that adding the LL factor substantially improves the pricing quality.

More precisely, in each graph we explicitly label the ten industries with the highest pricing errors in their respective models and report the associated mean-squared pricing errors. As we turn our attention to the panels on the right, we can see that when the LL factor is included, the predicted average excess returns of these industries move much closer to the realized values. As a result, our factor does particularly well for those industries that can be considered outliers in the CAPM and the FF3 model.

To quantify the additional pricing power of our LL factor, we show the overall mean squared pricing error (MSE) as well as the average of the ten largest pricing errors (MSE_{10}) above each of the two graphs. Several observations are important here. First, adding SMB and HML to the CAPM decreases the overall MSE from 4.14 to 2.60, whereas adding just LL reduces the average squared pricing error to 2.01, i.e., MSE declines by more than 50 percent.[10] The effect is even more pronounced for the industries with ten largest CAPM pricing errors: adding LL to the CAPM reduces MSE_{10} by about 60 percent.

The effect of introducing LL remains strong also with respect to the FF3 model. Adding our factor to the FF3 model reduces overall average squared pricing errors by about one third (from 2.60 to 1.73). For the ten industries with the largest pricing errors, the gain in pricing quality is slightly larger, in the order of 40% (with pricing errors declining from 6.46 to 3.67). Overall, these numbers provide additional evidence that the timing of risk is priced in the cross section of industry returns.

Portfolios sorted on firm-level LL-exposure. Our analysis shows that there is a positive link between the exposure of the returns of leading industries to the LL factor and the LL indicator. Here we take this link seriously and use the firm-level exposure to the LL 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.

Our results are reported in Table 10 (top portion of each panel) and confirm what we had found in our analysis with industries: the LL factor is priced and it enters the discount factor in an independent and significant way.

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

[10] The root-mean-squared error ($RMSE$) can be obtained as follows: $RMSE = 12 \cdot \sqrt{MSE/100}$. For the CAPM, for example, this value is 2.44.

[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.

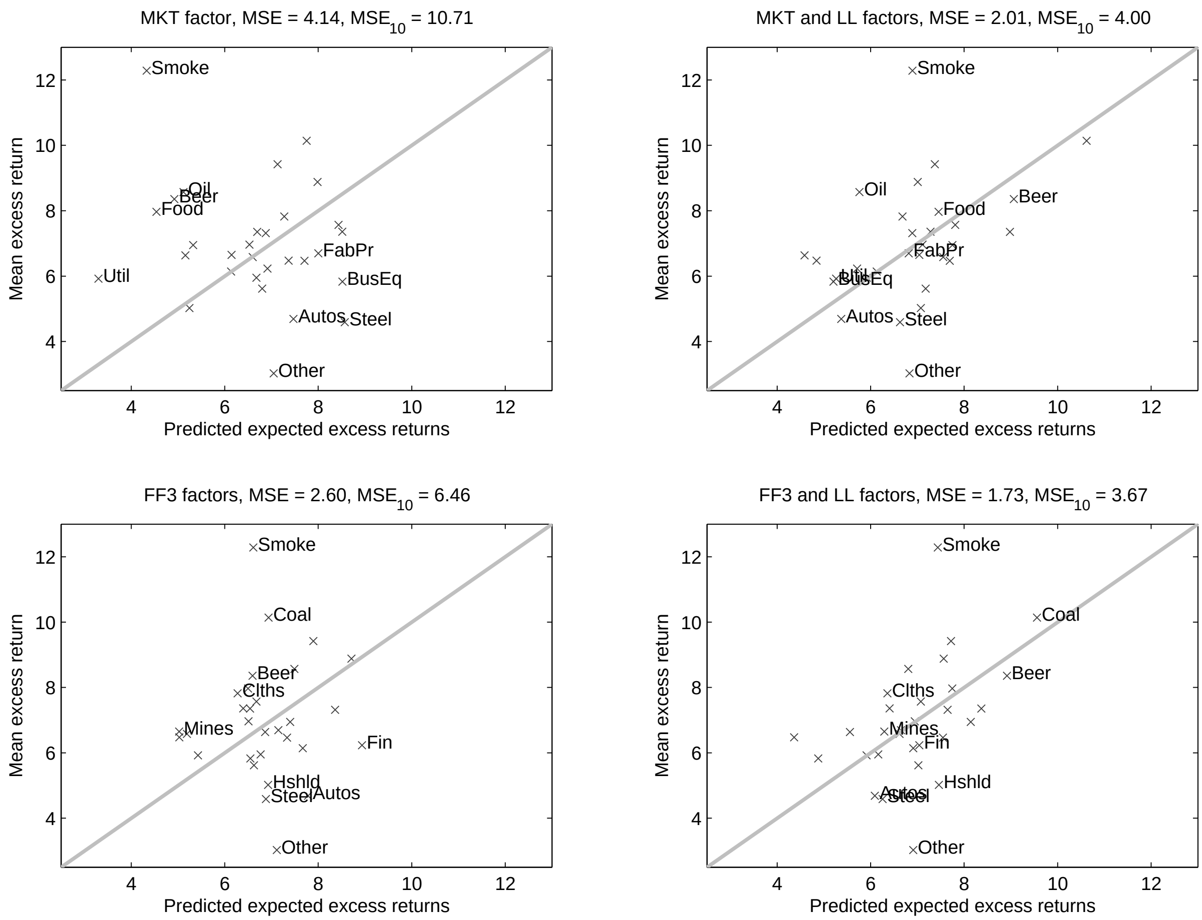

Fig. 2: Predicted vs. Realized Average Excess Returns for 30 Industries

This figure presents realized average excess returns (y-axis) for 30-industry portfolios plotted against the predicted mean excess returns from linear factor models (x-axis). Monthly returns are multiplied by 1200. We compare the performance of the CAPM and FF3 models with and without the addition of our lead-lag factor (LL). In the top two panels, we highlight 10 industries: the top 5 with a positive deviation from the 45-degree line, and the top 5 with a negative deviation. In the bottom two panels, we select the 10 industries in a similar way, but with respect to the FF3 model. MSE and MSE_{10} stand for mean squared error and are computed using all the 30-industry portfolios and the 10-industry portfolios with the largest absolute pricing errors, respectively. The MSE is computed in percent monthly returns and multiplied by 100.

confirms that the LL factor is still priced in the cross-section and represents a significant component of the discount rate.

3 A Rational Explanation of the Leading Premium

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

Table 10: Prices of Risk and Pricing Kernel Loadings – LL Cross Section

$E[R_i^{ex}] = \beta_{MKT}\lambda_{MKT} + \beta_{SMB}\lambda_{SMB} + \beta_{HML}\lambda_{HML} + \beta_{LL}\lambda_{LL}$			
λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{LL}
	30 LL-portfolios		
0.65***	0.85	0.49	1.05**
(0.19)	(0.57)	(0.40)	(0.53)
	38×3 LL-portfolios		
0.73***	0.32	-0.30	0.66*
(0.20)	(0.27)	(0.21)	(0.34)
	49×2 LL-portfolios		
0.63***	-0.17	0.12	0.95*
(0.17)	(0.20)	(0.21)	(0.51)
$m_t = \overline{m} - b_{MKT}MKT_t - b_{SMB}SMB_t - b_{HML}HML_t - b_{LL}LL_t$			
b_{MKT}	b_{SMB}	b_{HML}	b_{LL}
	30 LL-portfolios		
0.05***	0.1	0.09**	0.11**
(0.02)	(0.06)	(0.05)	(0.06)
	38×3 LL-portfolios		
0.04***	0.02	-0.01	0.08**
(0.01)	(0.04)	(0.03)	(0.04)
	49×2 LL-portfolios		
0.06***	-0.04*	0.02	0.11**
(0.01)	(0.03)	(0.03)	(0.05)

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 (4)–(5). 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. 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.

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:

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

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 what follows, 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.

An equilibrium model. We provide a rational explanation of our leading premium in an equilibrium model featuring two main elements: (a) an information structure affected by leads and lags of cash flows; 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:

$$\Delta c_{t+1} = \mu + x_{t-j_c} + \varepsilon_{t+1}^c \tag{7}$$

$$x_{t+1} = \rho x_t + \varepsilon_{t+1}^x \tag{8}$$

$$\Delta d_{t+1}^{lead} = \mu + \phi_x^{lead} x_t + \phi_0^{lead} \varepsilon_{c,t+1} + \varepsilon_{t+1}^{d,lead} \tag{9}$$

$$\Delta d_{t+1}^{lag} = \mu + \phi_x^{lag} x_{t-j_d} + \sum_{f=0}^{j_{lag}} \phi_f^{lag} \varepsilon_{c,t+1-f} + \varepsilon_{t+1}^{d,lag}, \tag{10}$$

where

$$v_{t+1} = \begin{pmatrix} \varepsilon_{t+1}^c \\ \varepsilon_{t+1}^x \\ \varepsilon_{t+1}^{d,lead} \\ \varepsilon_{t+1}^{d,lag} \end{pmatrix} \sim \mathcal{N}.i.i.d.(0,\Sigma), \quad \text{and } \Sigma = diag(\sigma_c^2, \sigma_x^2, \sigma_{d,lead}^2, \sigma_{d,lag}^2).$$

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.

The endogenous returns associated with this log-linear setting are reported in Appendix C. 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 (8).[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 these cash flows on leads and lags of both short- and long-run consumption news, consistent with equations (9)–(10). We use adjusted R^2 to optimally pin down the maximum number of leading/lagging periods, as detailed in Appendix B. We set statistically insignificant coefficients to zero.

We summarize our main results in Table 11. 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 B1 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. 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, 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.

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

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

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 (7). 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. Furthermore, when we remove advance information by setting $j_c = j_d = 0$, this premium declines to 1.65%. That is, advance information alone is responsible half of the model-implied LL premium. The remaining portion of the premium is driven by heterogeneous exposure to the long-run component ($\phi_x^{lead} > \phi_x^{lag}$).

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 enhanced, as the LL premium is even closer to its empirical counterpart.

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

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

[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 11: 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 (7)–(10). 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 B1. 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.

Table 12: 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 (7)–(10). 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.

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 C, 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.

Specifically, we let the dividends for cash flow i follow the dynamics specified in equation (10) 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 (9)–(10) and report the new estimates in Table 12. 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 12. 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:

$$\begin{aligned} E[R_i^{ex}] &= \beta_{i,MKT}\lambda_{MKT} + v_i, \\ E[R_i^{ex}] &= \beta_{i,LL}\lambda_{LL} + v_i, \\ E[R_i^{ex}] &= \beta_{i,MKT}\lambda_{MKT} + \beta_{i,LL}\lambda_{LL} + v_i, \end{aligned} \tag{11}$$

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

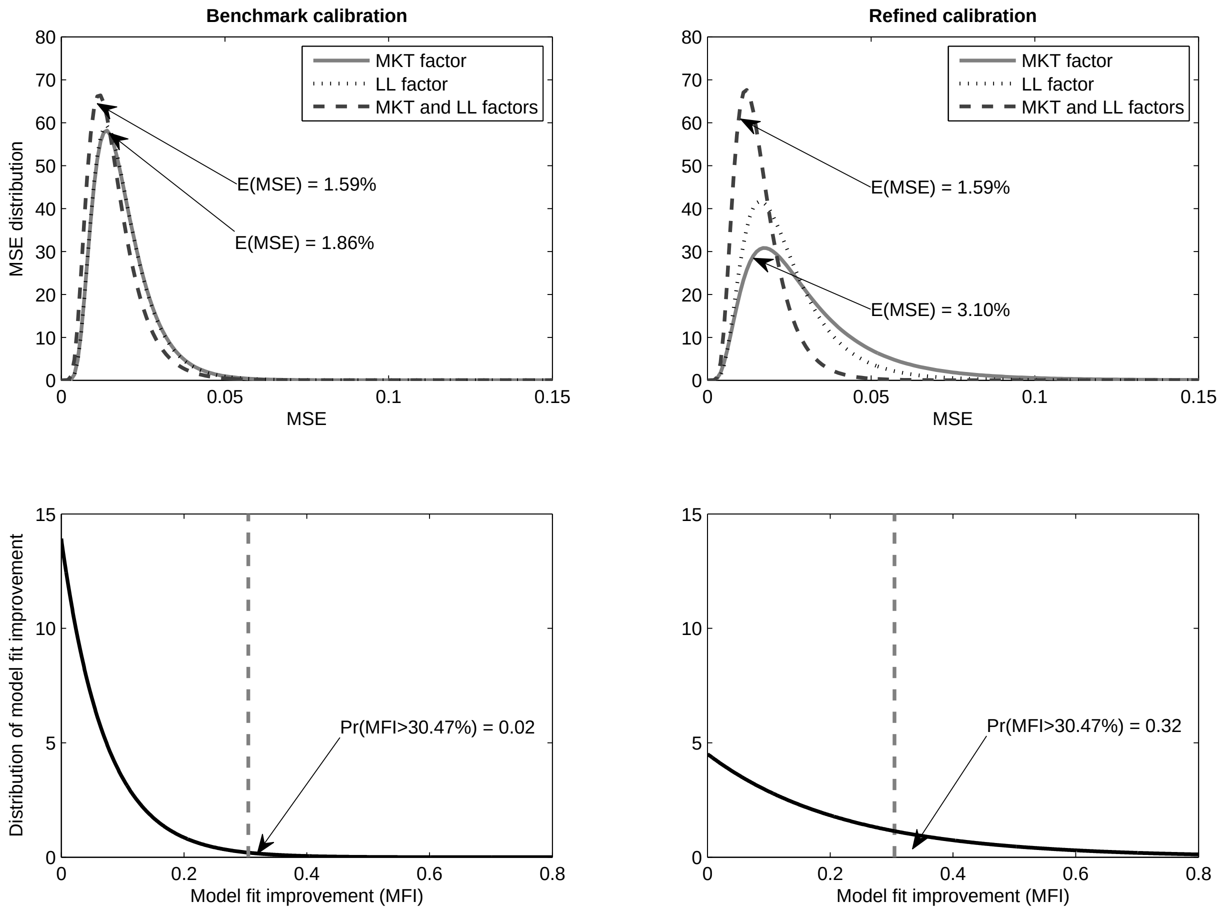

Fig. 3: Mean Squared Error (MSE) Distribution

This figure examines the goodness of fit of the factor models described in the system of equations (11). 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%.

down the LL indicator. Our main results are reported in Table 13. 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

Table 13: 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 3 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.

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.

4 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.

We construct a novel factor, denoted as LL, by considering the returns on a zero-cost portfolio long in leading and short in lagging firms. Our LL factor is priced in the cross section of industry portfolio returns, and it has a significant loading in a model with a linear stochastic discount factor in which the FF3 factors are included as well.

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 either by considering other classes of financial securities, such as bonds and options, or by examining international markets. A richer set of preferences could also be examined, including those in Caplin and Leahy (2001).

References

Acharya, V., H. Almeida, F. Ippolito, and A. Perez. 2014. Credit lines as monitored liquidity insurance: Theory and evidence. *Journal of Financial Economics* 112(3):287 – 319.

Ai, H. Information quality and long-run risks: Asset pricing and welfare implications. Unpublished 2007.

Ai, H., and R. Bansal. Risk Preferences and the Macroeconomic Announcement Premium. NBER working paper 2016.

Ai, H., M. M. Croce, A. Diercks, and K. Li. 2017. News shocks and the production-based term structure of equity returns. *Review of Financial Studies*. Forthcoming.

Albuquerque, R., and J. Miao. 2014. Advance information and asset prices. *Journal of Economic Theory* 149:236–275.

Asness, C., A. Frazzini, and L. Pedersen. 2014. Low-risk investing without industry bets. *Financial Analysts Journal* 70(1):24–41.

Bansal, R., and A. Yaron. 2004. Risks for the long run: A potential resolution of asset pricing puzzles. *Journal of Finance* 59(4):1481–1509.

Bansal, R., R. F. Dittmar, and C. T. Lundblad. 2005. Consumption, dividends, and the cross section of equity returns. *Journal of Finance* 60(4):1639–1672.

Belo, F., P. Colin-Dufresne, and R. Goldstein. 2014. Dividend dynamics and the term structure of dividend strips. *The Journal of Finance* 70(3).

Binsbergen, J., and R. S. Koijen. 2017. The term structure of returns: facts and theory. *Journal of Financial Economics* 124(1):1–21.

Binsbergen, J., M. W. Brandt, and R. S. Koijen. 2012. On the timing and pricing of dividends. *American Economic Review* 102(4):1596–618.

Binsbergen, J., W. H. Hueskes, R. S. Koijen, and E. B. Vrugt. 2013. Equity yields. *Journal of Financial Economics* 110(3):503–19.

Campbell, J. Y., and R. J. Shiller. 1988. Stock prices, earnings, and expected dividends. *Journal of Finance* 43(3):661–676.

Caplin, A., and J. Leahy. 1993. Sectoral shocks, learning, and aggregate fluctuations. *Review of Economic Studies* 60(4):777–794.

Caplin, A., and J. Leahy. 1994. Business as usual, market crashes, and wisdom after the fact. *American Economic Review* 84(3):548–565.

Caplin, A., and J. Leahy. 2001. Psychological expected utility theory and anticipatory feelings. *Quarterly Journal of Economics* 116(1):55–79.

Carhart, M. M. 1997. On persistence in mutual fund performance. *Journal of Finance* 52(1):57–82.

Cochrane, J. H. *Asset Pricing – Revised Edition.* Princeton University Press Princeton, NJ 2005.

Cochrane, J. H., and M. Piazzesi. 2005. Bond risk premia. *American Economic Review* 95(1): 138–160.

Croce, M. M. Welfare costs in the long run. Working Paper 2013.

Croce, M. M., M. Lettau, and S. C. Ludvigson. 2014. Investor information, long-run risk, and the duration of risky cash-flows. *Review of Financial Studies* 28(3):706–742.

Epstein, L. G., and S. E. Zin. 1989. Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework. *Econometrica* 57(4):937–69.

Epstein, L. G., Farhi, Emmanuel, and T. Strzalecki. 2014. How much would you pay to resolve long-run risk? *American Economic Review* 104(9):2680–97.

Estrella, A., and F. S. Mishkin. 1998. Predicting us recessions: Financial variables as leading indicators. *Review of Economics and Statistics* 80(1):45–61.

Fama, E. F., and K. R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33(1):3–56.

Fama, E. F., and K. R. French. 1997. Industry costs of equity. *Journal of Financial Economics* 43 (2):153–193.

Fama, E. F., and K. R. French. 2012. Size, value, and momentum in international stock returns. *Journal of Financial Economics* 105(3):457–472.

Fama, E. F., and K. R. French. 2015. A five-factor asset pricing model. *Journal of Financial Economics* 116(1):1–22.

Gofman, M., G. Segal, and Y. Wu. Production networks and stock returns: The role of creative destruction. Working Paper 2017.

Gomes, J. F., L. Kogan, and M. Yogo. 2009. Durability of output and expected stock returns. *Journal of Political Economy* 117(5):941–986.

Gomme, P., F. E. Kydland, and P. Rupert. 2001. Home production meets time to build. *Journal of Political Economy* 109(5):1115–1131.

Greenwood, J., and Z. Hercowitz. 1991. The allocation of capital and time over the business cycle. *Journal of Political Economy* 99(6):1188–1214.

Hong, H., W. Torous, and R. Valkanov. 2007. Do industries lead stock markets? *Journal of Financial Economics* 83(2):367–396.

Hou, K., C. Xue, and L. Zhang. 2015a. Digesting anomalies: An investment approach. *Review of Financial Studies* 28(3):650–705.

Hou, K., C. Xue, and L. Zhang. A comparison of new factor models. Working Paper 2015b.

Jurado, K., S. C. Ludvigson, and S. Ng. 2015. Measuring uncertainty. *American Economic Review* 105(3):1177–1216.

Kadan, O., and A. Manela. Estimating the value of information. Working Paper 2016.

Kendall, M. 1954. Note on bias in the estimation of autocorrelation. *Biometrika* 41(3-4):403–404.

Kogan, L., and D. Papanikolaou. 2014. Growth opportunities, technology shocks, and asset prices. *Journal of Finance* 69(2):675–718.

Koijen, R. S., H. Lustig, and S. Van Nieuwerburgh. 2017. The cross-section and time series of stock and bond returns. *Journal of Monetary Economics* 88:50–69.

Lettau, M., and J. A. Wachter. 2007. Why Is Long-Horizon Equity Less Risky? A Duration-Based Explanation of the Value Premium. *Journal of Finance* 62(1):55–92.

Lettau, M., and J. A. Wachter. 2011. The Term Structure of Equity and Interest Rates. *Journal of Financial Economics* 101(1):90–113.

Lettau, M., M. Maggiori, and M. Weber. 2014. Conditional risk premia in currency markets and other asset classes. *Journal of Financial Economics* 114(2):197 – 225.

Lucas, R. E. *Models of business cycles* volume 26. Basil Blackwell Oxford 1987.

Moskowitz, T. J., and M. Grinblatt. 1999. Do industries explain momentum? *Journal of Finance* 54(4):1249–1290.

Newey, W., and K. West. 1987. A simple, positive definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55(3):703–708.

Patton, A., and M. Verado. 2012. Does beta move with news? firm-specific information flows and learning about profitability. *Review of Financial Studies* 25(9):2789–2839.

Savor, P., and M. Wilson. 2013. How much do investors care about macroeconomic risk?evidence from scheduled economic announcements. *Journal of Financial and Quantitative Analysis* 48(2): 343–375.

Savor, P., and M. Wilson. 2016. Earnings announcements and systemic risk. *Journal of Finance* 71(1):83–138.

Stambaugh, R. Bias in regressions with lagged stochastic regressors. Working Paper 1986.

Stock, J. H., and M. W. Watson. New indexes of coincident and leading economic indicators. In *NBER Macroeconomics Annual 1989, Volume 4* pages 351–409. MIT Press Cambridge, MA 1989.

Stock, J. H., and M. W. Watson. 2002. Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics* 20(2):147–162.

Torous, W., R. Valkanov, and S. Yan. 2004. On predicting stock returns with nearly integrated explanatory variables. *Journal of Business* 77(4):937–966.

Valkanov, R. 2003. Long-horizon regressions: theoretical results and applications. *Journal of Financial Economics* 68(2):201 – 232.

Appendices

A 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 the Kenneth French's website.

Table A1: 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 2. 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 A2: 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 A3: 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	0.20	0.12	0.25	0.18

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. 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 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 A4: 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 (4)–(5). 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.

Table A5: Mean Squared Error of Linear Asset Pricing Models

Model	30 industries	38 industries	49 industries
MKT	4.14	4.13	4.85
MKT+LL	2.01	2.97	3.35
FF3	2.60	3.06	3.52
FF3+LL	1.73	2.53	2.52

Notes: This table reports the mean squared errors (MSE) associated to the model defined in equations (4)–(5) using 30, 38, and 49 industry portfolios as test assets, repsectively. The entries associated to MKT refer to a one-factor model with only market excess returns. MKT+LL includes both the lead-lag factor and the market excess return. The row FF3 (FF3+LL) refers to the MSEs of the FF3 factors model (augment with our LL factor). Monthly data start in 1972:01 and end in 2012:12. MSEs are computed on percent monthly returns and then are multiplied by 100.

Table A6: 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 in parentheses. Monthly data start in 1972:01 and end in 2010:12. The TMB factor is available starting from 2003:11.

Table B1: 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.

B Cash-Flow Dynamics

This section provides further details about the estimation of the cash flows described in equations (7)–(10). 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 or, equivalently, to minimize the companion F-statistics. 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 B1.

C Solution of the Model

In this section, we present derivations of the model solution in a general form. The consumption dynamics (7) can be written in the following generalized format:

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

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 $\mathbb{I}_t = \left\{ x_{t-j_c}, \{\varepsilon^x_{t+1-i}, i = 1, .., j_c\}, \{\varepsilon^c_{t-f}, f = 1, .., f_c\} \right\}$.

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:

$$s_t^x = \underbrace{\begin{bmatrix} x_{t-j_c} \\ \varepsilon^x_{t-j_c+1} \\ \vdots \\ \varepsilon^x_t \end{bmatrix}}_{N_1\times 1}, \quad s_t^c = \underbrace{\begin{bmatrix} \varepsilon^c_{t-f_c} \\ \varepsilon^c_{t-f_c+1} \\ \vdots \\ \varepsilon^c_t \end{bmatrix}}_{N_2\times 1}, \quad N = N_1 + N_2. \tag{C.2}$$

The dynamics of the state vector can be described as

$$\begin{aligned} s^x_{t+1} &= \underbrace{\begin{bmatrix} \rho & 1 & 0 & \dots & 0 & 0 \\ 0 & 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & 0 & 1 \\ 0 & 0 & 0 & \dots & 0 & 0 \end{bmatrix}}_{\Lambda^x} s^x_t + \underbrace{\begin{bmatrix} 0 & 0 \\ 0 & 0 \\ \vdots & \vdots \\ 0 & 0 \\ 1 & 0 \end{bmatrix}}_{\Omega^x} \begin{bmatrix} \varepsilon^x_{t+1} \\ \varepsilon^c_{t+1} \end{bmatrix} \\ s^c_{t+1} &= \begin{bmatrix} \varepsilon^c_{t-f_c+1} \\ \varepsilon^c_{t-f_c} \\ \vdots \\ \varepsilon^c_t \\ \varepsilon^c_{t+1} \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & 1 & 0 & \dots & 0 & 0 \\ 0 & 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & 0 & 1 \\ 0 & 0 & 0 & \dots & 0 & 0 \end{bmatrix}}_{\Lambda^c} s^c_t + \underbrace{\begin{bmatrix} 0 & 0 \\ 0 & 0 \\ \vdots & \vdots \\ 0 & 0 \\ 0 & 1 \end{bmatrix}}_{\Omega^c} \begin{bmatrix} \varepsilon^x_{t+1} \\ \varepsilon^c_{t+1} \end{bmatrix} \\ s_{t+1} &= \begin{bmatrix} \Lambda^x & 0 \\ 0 & \Lambda^c \end{bmatrix} s_t + \begin{bmatrix} \Omega^x \\ \Omega^c \end{bmatrix} \begin{bmatrix} \varepsilon^x_{t+1} \\ \varepsilon^c_{t+1} \end{bmatrix}. \end{aligned}$$

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

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

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

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

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

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

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

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

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 (C.5) can be rewritten as follows:

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

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:

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

Similarly to equation (C.1), the dividend growth dynamics (9)–(10) can be represented as

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

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:

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

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:

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

C.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:

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

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

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 $\left\{ \varepsilon^x_{t-j_c+1}, \ldots, \varepsilon^x_t \right\}$. 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

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

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 (C.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 as follows:

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

Note that (C.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:

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

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 that 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

$$\begin{aligned} r^d_{t+1} &= \overline{r^d} + \tfrac{1}{\psi}x_{t-j_c} + \tfrac{\kappa_d\left(\phi_x - \frac{1}{\psi}\kappa_d^{j_c}\right)}{1-\kappa_d\rho}\varepsilon^x_{t+1} + \varepsilon^d_{t+1} \\ E_t[r^{ex,d}_{t+1}] &= -\text{cov}(m_{t+1} - E_t[m_{t+1}], r^d_{t+1} - E_t[r^d_{t+1}]) \\ &= \tfrac{\kappa_c^{j_c+1}\kappa_d\left(\phi_x - \frac{1}{\psi}\kappa_d^{j_c}\right)\left(\gamma-\frac{1}{\psi}\right)}{(1-\kappa_c\rho)(1-\kappa_d\rho)}\sigma^2_x. \end{aligned}$$

Assuming a preference for the early resolution of uncertainty ($\gamma > \frac{1}{\psi}$) and an IES greater than

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.[16] With increasing j_c the dividend claim exhibits more and more information risk relative to the consumption claim, which generates an increasing information premium as a component of the expected excess return.

C.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 the 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

$$\Delta c_{t+1} = \mu + x_t + \varepsilon^c_{t+1} \tag{C.12}$$

$$x_{t+1} = \rho x_t + \varepsilon^x_{t+1} \tag{C.13}$$

$$\Delta d_{t+1} = \mu + \phi_x x_t + \phi_f \varepsilon^c_{t+1-f} + \varepsilon^d_{t+1}, \tag{C.14}$$

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:

$$\begin{aligned} m_{t+1} &= \overline{m} - \tfrac{1}{\psi}x_t - \gamma\varepsilon^c_{t+1} - \left(\gamma - \tfrac{1}{\psi}\right)\tfrac{\kappa_c}{1-\kappa_c\rho}\varepsilon^x_{t+1} \\ r^c_{t+1} &= \overline{r^c} + \tfrac{1}{\psi}x_t + \varepsilon^c_{t+1} + \left(1 - \tfrac{1}{\psi}\right)\tfrac{\kappa_c}{1-\kappa_c\rho}\varepsilon^x_{t+1} \\ r^f_t &= \overline{r^f} + \tfrac{1}{\psi}x_t. \end{aligned} \tag{C.15}$$

Next, consider the dividend claim with cash-flow dynamics specified in equation (C.14). Conjecturing that the price-dividend ratio is linear in all state variables and using the Euler equation, we find that the return on this claim is given as follows:

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

[16] 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.

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

$$\begin{aligned} E_t[r_{t+1}^{ex,d}] &= -\text{cov}(m_{t+1} - E_t[m_{t+1}], r_{t+1}^d - E_t[r_{t+1}^d]) \\ &= \gamma \phi_f \kappa_d^{f+1} \sigma_c^2 + \frac{\kappa_c \kappa_d \left(\phi_x - \frac{1}{\psi}\right)\left(\gamma - \frac{1}{\psi}\right)}{(1-\kappa_c \rho)(1-\kappa_d \rho)} \sigma_x^2, \end{aligned}$$

implying that advance information on the short-run shock reduces the required risk premium, although to a much more modest extent.

D A Diffusion Model

Consider and economy with $i = 1, ..., N \geq 3$ industries, or, equivalently, firms. 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:

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

This means that $f(i,j)$ 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:

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

and define aggregate GDP as:

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

We set our parameters in order to replicate key properties of US GDP. Specifically, we set $\rho = .90$ 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. The quarterly drift μ is set to 0.50%.

We show a representative quarterly simulation of this model in Figure D1. 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.

In order to better highlight the mechanism at play, we assume that firm 1 is affected by a pronounced positive shock at time 20 and that firm 11 is affected by a pronounced negative shock at time 80. This allows us to know exactly which firm 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 D1 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 firm 1 (firm 11) at time 20 (time 80). The growth rate of firm 1 (firm 11) leads the peak (trough) of aggregate growth by $(N-1)/2 = 15$ quarters. The cash flow of firm 11 (firm 1) lags that of firm 1 (firm 11) by 10 periods.

As shown in the bottom panels of Figure D1, 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 firm 1 starts to increase within a few quarters from the realization of our positive shocks. For about 20 quarters, firm 1 is correctly identified as strongly leading GDP growth. The same holds with firm 11, since it is identified as leading the recession

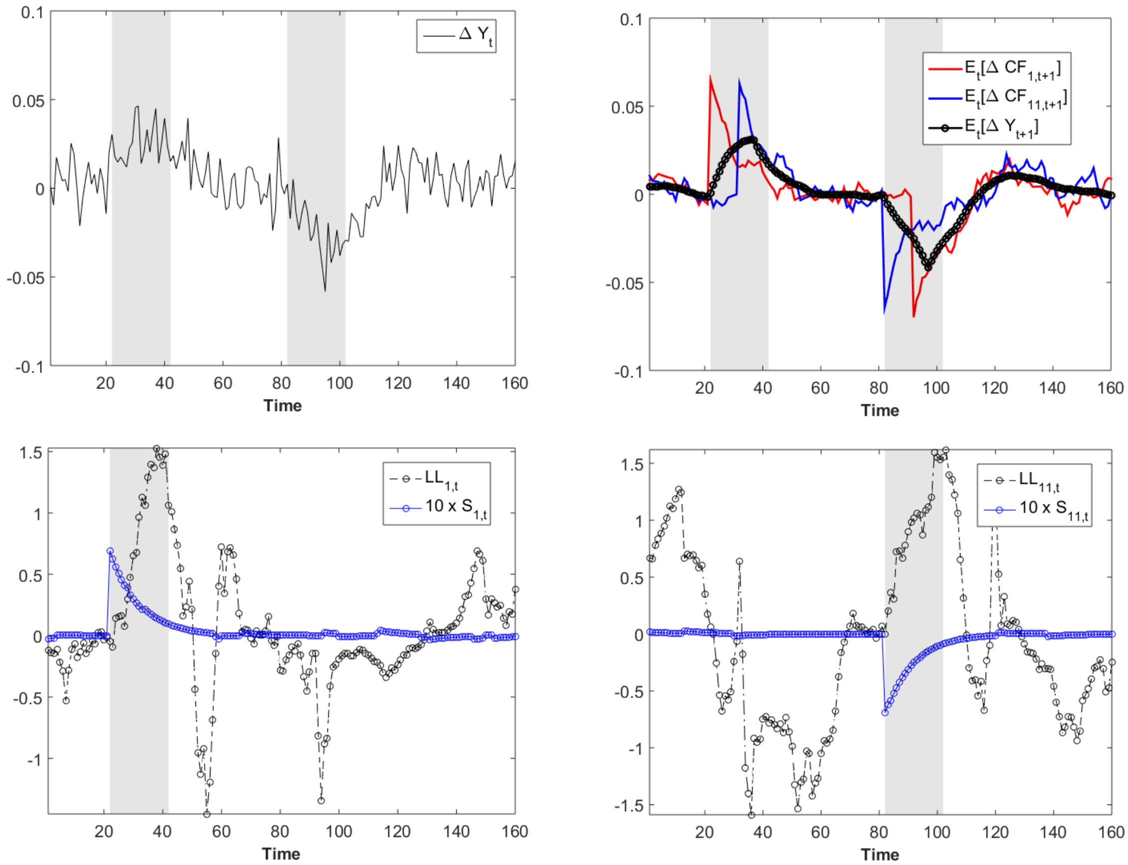

Fig. D1: Simulation from Diffusion Model

This figure depicts a quarterly simulation from the diffusion model described in Section D. 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:

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

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

episode occurring after period 80. Simultaneously, during this recession firm 1 is classified as lagging firm because its LL indicator declines.