Labor Market Networks and Asset Returns*

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Abstract

This paper proposes a measure of labor market connectivity based on the similarity in the composition of occupational knowledge characteristics across industries and provides evidence of return predictability in the cross-section of industries that are connected through the labor market. In long-short portfolios, an industry's return is strongly predicted by the past return of its labor-market-connected neighboring industries with an annualized return of up to 9%, which is not explained by established asset pricing models. The return predictability remains significant after controlling for the supply chain momentum as well as the industry lead-lag effect, and is concentrated in stocks with higher arbitrage costs and higher ownership of uninformed investors. We find similar predictive relations for the labor productivity, wages, employment, and profitability of labor connected industries. Our findings are consistent with positive spillover of productivity shocks among industries that are connected through the labor market. Informational frictions, costly arbitrage, and investors' limited attention magnify the delayed response of stock prices to the spillover of labor productivity shocks, which results in the observed return predictability.

Keywords: Labor network, labor productivity, cross section of stock returns.
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1 Introduction

Understanding the impact of knowledge (technology) spillovers on economic growth and productivity has been a topic of long-lasting interest in macro-finance literature. For example, an influential article by Bloom, Shankerman, and VanReenen (2013) provides a framework to understand two countervailing spillover effects: a positive effect of technology spillover and a negative effect of product market competition. They find a dominating effect of technology spillover and call for more research to understand the specific mechanisms of knowledge spillover. Extending this line of research, we focus on a crucial factor of firm production activities, the labor force, and study the impact of knowledge spillover on asset prices and real quantities in the labor market network that connects the labor forces across different industries in the U.S.

One of our objectives is to introduce a measure of labor market connectivity based on the similarity in the composition of occupational knowledge characteristics. Firms with overlapping labor knowledge requirements interact with each other in the labor market through competition for similar talents or adaptation of technologies that enhances the productivity of a common subset of their employees. For example, financial industry and technology industry have been competing fiercely for technology-related talents in recent years.[1] We characterize the occupations in each industry by combining the industry occupation composition from the Bureau of Labor Statistics' Occupational Employment Statistics (OES) dataset with the individual occupation characteristic from O*NET. We first assign each individual industry a vector of knowledge characteristic scores across jobs in that industry. Then, we measure the labor market connectivity (henceforth LC) of an industry pair as the closeness of the job characteristic score vectors for the two industries.[2]

[1] See, for example, https://www.businessinsider.com/wall-street-feeds-on-silicon-valley-to-fill-voracious-tech-appetite-2019-1.

[2] Specifically, each element in the industry score vector is constructed as the labor expenditure-weighted average of the scores associated with the occupations in that industry. We will measure the proximity between each industry pair using the Euclidean distance between their characteristic score vectors.

Our approach to measure LC is based on the occupational characteristic of industries, since these characteristics are what determine the facility at which workers can transition from one occupation to another. In other words, two occupations with similar occupational characteristics are likely to employ the same type of workers relative to a pair of occupations with different required areas of knowledge. After sorting industries into LC quintiles, we find that industry pairs in each LC quintile has between 69% and 87% probability to stay in the same quintile in the next three years. However, we also find that the industry pairs have about 10% probability of transitioning to the neighboring quintile, due to evolving human capital and technologies. In addition, we find that the correlation between LC and other forms of economic linkages, including the customer-supplier relationship as well as geographical closeness, is relatively small. Moreover, we find that there is only a 10.5% probability that company pairs in the highest LC quintile are in the same sectors. These findings suggest that our proposed measure captures a different form of economic connectivity than the other connectivity forms that have been underscored in previous studies.

Two counter economic forces can shape the impact of productivity shock transmission through the labor market network on asset prices and real quantities. On one hand, industries with overlapping labor types could be subject to similar labor-productivity shocks to their connected industries, thus generating a positive spillover effect. Such labor-productivity shocks can be due to the labor market friction shocks that affect how labor is organized (e.g., wage setting, hiring and firing policies, etc) for certain labor force, or the technology shocks that change the efficiency of labor input. On the other hand, there potentially exists a negative spillover effect due to the competitions for talent. For instance, a negative idiosyncratic demand shock to an industry may result in layoffs in this industry, which could increase the supply of labor in specific segments of the market and hence reduce labor market tightness for labor with particular skill sets. This, in turn, can boost employment and productivity for other industries with similar labor composition due to lower per unit labor cost, leading to a negative spillover effect. Both the positive and negative spillover effects can be related to the line of work that highlights the role of knowledge spillover in enhancing productivity of firms that are otherwise competing against each other (e.g., Bloom et al. (2013)). In this paper, we examine the specific channel of spillovers through the labor market.

Our main empirical analyses focus on understanding how productivity shocks are transmitted across firms through the labor market linkages. We investigate this through the lens of stock returns and real quantities.

Specifically, for each subject industry, we construct its Labor Connected Industry portfolio return (henceforth *LCI* return) as the weighted average of all other industry returns weighted by their corresponding *LC* between the subject industry and each of the other industries. We find a significantly positive link between the return of an industry and the lagged return of its corresponding *LCI* portfolio. In particular, industries whose *LCI* past returns are in the top quintile outperform their peers in the bottom quintile by 5.19% (9.23%) per year in the value-weighted (equal-weighted) portfolios, a pattern that persists over our sample period.[3]

Importantly, this return spread is not explained by established factor models, such as the Fama and French (1993) and Carhart (1997) 4-factor model, Fama and French (2015) 5-factor model, the q-factor model of Hou, Xue, and Zhang (2015), the mispricing factor model of Stambaugh and Yuan (2017), and the behavioral factor model of Daniel, Hirshleifer, and Sun (2020). The long-short portfolio's alpha from these models is in the range of 3.53% and 5.53% per year. Moreover, using Fama-MacBeth regressions, we show that our documented *LCI* return predictability is not due to the subject industry's past returns (i.e., industry return momentum) or the input-output network (the supply-chain return diffusion).

To understand whether the industry return predictability is driven by systematic or

[3] We find that the *LCI* return predictability is persistent for three months into the future. In addition, we find even more significant alphas for the equal-weighted long-short portfolios, ranging from 7.13% to 9.86% per annum with t-statistics between 3.60 and 5.85.

macroeconomic risk, we investigate if the portfolio returns can be explained by the industry exposures to various macroeconomic shocks in a generalized method of moments (GMM) framework using the *LCI* quintile portfolios as the test assets. However, we find that a pricing kernel that consists of the excess market return and the macroeconomic shocks has very limited power in explaining the observed portfolio returns. Thus, we next test whether the findings can be explained by informational frictions and/or limits to arbitrage. We find supporting evidence for mispricing, rather than compensation for risk. Specifically, we find that the *LCI* return predictability is concentrated in firms that receive less investor attention and largely held by uninformed investors (proxied by lower analyst coverage or lower institutional ownership). These results suggest the *LCI* return predictability is likely due to informational frictions that prevent the shocks transmitting through the labor network from being incorporated into stock prices immediately.

Our analysis on stock returns reveals a positive return spillover effect in the labor market network. Our next set of tests aims at understanding the impact of shock transmission through the labor market network on real quantities. These analyses also enable us to understand the economic underpinnings of return spillover and predictability. First, we find a spillover effect on hiring policies. Specifically, we find that the focal industry's wage growth, employment growth, and total labor expenses' growth are higher when its *LCI*'s past corresponding labor quantities (or stock returns) are higher. Second, we find that the focal industry's labor productivity growth is positively predicted by its *LCI*'s past labor productivity growth, but the spillover effect does not hold for capital productivity growth. In addition, we find a similar positive spillover effect on profitability. These findings suggest that the positive spillover effect of labor productivity shock dominates the negative spillover effect of competition for labor force in the labor market network.

Last but not least, we analyze what types of industries are more likely to benefit from the labor productivity spillover. In general, we find that industries that have a greater capacity to absorb the shock benefit more. For example, the *LCI*'s return predictability is stronger when the subject industry has higher profitability and is more innovative. Similarly, the predictability is strongest among industries with greater labor mobility (Donangelo (2014)), in line with the idea that these industries generally face lower labor adjustment costs in response to productivity shocks.

Our paper contributes and bridges two strands of the literature. First, it adds to the literature on labor and asset pricing.[4] Specifically, it builds on the studies that investigate the (standalone) labor heterogeneity as a determinant of asset returns in the cross-section. Belo, Li, Lin, and Zhao (2017), for instance, show that firms in industries with a greater reliance on high-skilled workers would face a greater labor adjustment cost, giving rise to a more pronounced hiring-expected return relationship. Kilic (2017) investigates the asset pricing implications of hiring demographics by linking firms' demographic adjustments to the level of technology that is embodied in new capital formation in its corresponding industry. Zhang (2019) studies the importance of firms' option to automate tasks, measured based on the occupational composition of firms, as a determinant of the cross-section of expected returns. In this framework, the option to replace routine-task labor with machines enables firms to reduce their exposure to systematic risk by increasing their efficiency during bad times. Our contribution to this strand of literature lies in establishing that labor heterogeneity can also induce fundamental connection between industries, giving rise to predictability in returns as well as real quantities across industries connected by the labor market network.

Second, we extend the growing literature on lead-lag effects in returns of fundamentally connected firms. Relative to this line of work, we introduce an important alternative channel through which firms can be fundamentally connected through the labor market based on the occupational characteristics of their existing labor force. The important finding in this literature is that informational frictions would delay the incorporation of value relevant information into the prices of fundamentally linked firms. These fundamental connections

[4]See, e.g., Eisfeldt and Papanikolou (2013), Belo, Lin, and Bazdresch (2014), Donangelo (2014), and Kuehn, Simutin, and Wang (2017).

can be the result of supply chain relationship between economic entities (Cohen and Frazzini (2008), Menzly and Ozbas (2010), and Grigoris and Segal (2021)), geographic proximity of firms' headquarters (Parsons, Sabbatucci, and Titman (2020)), co-analyst coverage of the stocks (Ali and Hirshleifer (2020)), and technological links between firms (Lee, Sun, Wang, and Zhang (2019)). We show that informational frictions induce return predictability across labor market connected industries, over and above what can be explained by the other established channels. In addition, recent research (e.g., Liu and Wu (2019), henceforth LW) has started exploring the effect of labor related network. Our paper complements Liu and Wu (2019) in important ways. For example, our labor network is based on the existing labor force of different industries, complementing the labor demand (job postings) based network proposed by LW.[5] This difference also leads to our finding of a positive labor productivity spillover effect which complements the negative labor market competition effect documented in LW.

The remainder of the paper is organized as follows. Section 2 describes the data and variables. Section 3 presents the main empirical results on the cross-sectional return predictability and examines its economic underpinnings. Section 4 further investigates the sources of industry return predictability based on the labor productivity shocks. Section 5 concludes the paper.

2 Data

In this section, we introduce the data and describe how we construct the labor market connectivity (LC) as the measure of fundamental relatedness between each pair of industry through the labor market. We then report a number of characteristics associated with this measure of inter-industry connectivity, including how it relates to and differentiates from

[5] While job postings could account for variations in our labor force based network measure, we find that the transition probability across our neighboring LC quintiles is only 10%, suggesting the relatively stable labor force based network differs from the job postings based network.

other channels through which shocks can propagate across industries.

2.1 Accounting Data and Asset Prices

Our sample includes common stocks (share code of 10 or 11) listed on NYSE, AMEX, and Nasdaq (exchange code of 1, 2 or 3) available at the Center for Research in Securities Prices (CRSP). We use accounting data from Compustat Fundamentals Annual to construct variables that represent various firm characteristics used in the tests. Our sample period covers the period between January 1990 and April 2017.[6] In the Appendix, we provide a more detailed description of the data and the accounting variables used in our empirical analyses.

2.2 Measuring Labor Market Connectivity

The key empirical variable in our analysis is the LC, which measures the extent to which types of labor employed by each pair of industries are similar to each other. Our measure relies on the fact that each occupation is defined by what knowledge is required in fulfilling the job duties, namely the occupation knowledge characteristics. The required work-related areas of knowledge are the set of principles that are applied to problems that are part of the job. Importantly, this characteristic is an important determinant of the facility at which workers can transition from one occupation to another. In other words, two occupations that are similar in work-related areas of knowledge are likely to be employing the same type of workers relative to a pair of occupations which have very different required areas of knowledge. This means that a suitable proxy for the labor market connectivity between two industries would encompass the similarity between the required work-related areas of knowledge in jobs that fall within those industries.

[6]Specifically, the annual accounting and labor data cover the sample period of 1990 to 2016. In our return predictability analysis, we predict monthly returns up to April 2017.

The U.S. Department of Labor dataset of Occupational Information Network (O*NET) provides scores that reflect of relevance of each area of knowledge in each occupation from an extensive list of the areas of knowledge for over 1,100 occupations in the US economy.[7] For each area of knowledge, O*NET provides information on the "importance" and "level" for each occupation. We follow Blinder (2009) and Firpo, Fortin, and Lemieux (2013) by combining these quantities using a Cobb-Douglas function with the arbitrary weights of one third for the "level" quantities and two thirds for the "importance" quantities. In other words, for each area of knowledge k and for occupation j, we construct a composite score s_{jk} as:

$$s_{jk} = I_{jk}^{\frac{2}{3}} L_{jk}^{\frac{1}{3}}, \tag{1}$$

where I_{jk} and L_{jk} denote, respectively, the "importance" and "level" quantities for each k and j available at O*NET. We then re-scale the score for each area of knowledge across all occupations to account for potential differences in the average score of different knowledge areas.

We next measure the importance of each area of knowledge for each industry by combining this data with the Bureau of Labor Statistics' Occupational Employment Statistics (OES) dataset, which includes information on the occupational composition of industries and their corresponding wages. Specifically, the dataset estimates employment in every occupation in each industry using surveys covering a stratified sample of 200,000 establishments every six months over three-year cycles from 1988 to 2016. Each industry is surveyed once every three years from 1988 to 1995, and every year from 1996 onward, resulting in the coverage of roughly 62% of total U.S. employment. Following Donangelo (2014), from 1988 to 1995 we combine surveys in each year with those in the previous two years to have a sample that covers all industries in each year. This sets the first year of our occupation employment data to 1990. For each year between 1996 and 2016, the dataset already contains the updated

[7]The areas of knowledge are classified into 33 categories, among which are "Food Production", "Computers and Electronics", "Sales and Marketing", etc.

employment data for that year along with the past two years.[8] The survey started to record hourly wage estimates for each occupation-establishment in 1997. For the period prior to this year, we follow Zhang (2019) by estimating the hourly wage for each occupation-industry from the Census Current Population Survey Outgoing Rotation Group (CPS-ORG) obtained from the NBER website.[9]

We make use of the occupation codes to match the occupations in the O*NET dataset with those in OES.[10] Using the merged dataset we define $c_{i,k,t}$ as the weighted-average significance score for area of knowledge k in industry i for year t as:

$$c_{i,k,t} = \frac{\sum_j e_{i,j,t} \times s_{j,k}}{\sum_i e_{i,j,t}}, \tag{2}$$

where $e_{i,j,t}$ is the labor expenditure associated with occupation j in industry i in year t. Our usage of labor expenditure for occupations as the weights in calculating the average score for each knowledge area at the industry level is consistent with variations in wages reflecting differences in productivity across different occupations. As a result, using labor expenditure, rather than the level of employment as the weight would signify the importance

[8]Due to BLS' change in survey methodology, the data in 1996 cover the survey conducted in the year 1996 only, and the data for 1997 cover surveys in 1996 and 1997. The cross-sectional nature of our study and the fact that the surveys are well stratified across industries still allow us to use the data in those years.

[9]For each industry-occupation in the OES dataset, we use the corresponding earnings-weighted average hourly wage of individuals aged 18 to 65 in its matching broad industry-occupation observations in CPS-ORG. To match the Census Occupation Codes (COC) used in CPS-MORG with OES occupational classification codes, we take a similar approach as Zhang (2019) by matching a COC to an OES occupation code if their corresponding matched SOC codes have an overlap of at least 50%. To crosswalk the Census Industry Codes with the 3-digits SIC codes, we use the table provided in http://unionstats.gsu.edu. For the industry-occupations that do not have a matching pair in the CPS-ORG data, we use the average hourly wage for that occupation in the one-digit SIC code. For the remaining missing occupation-industry wages, we use the national average of the wage for that occupation and the average industry wage, respectively.

[10]The OES uses its own five-digit taxonomy to identify occupations in its data prior to 1999, the six-digit 1999 OES taxonomy for the year 1999, and the 2000 SOC taxonomy from 2000 to 2009. From 2010 onward, occupations in this dataset are coded under the 2010 SOC taxonomy, which is the taxonomy used in O*Net and therefore the benchmark taxonomy used throughout our study. We use the cross-walk provided by the Analyst Resource Center to relate each OES-coded occupation to its corresponding occupation classified under the 2000 SOC code. We use the 2000-to-2010 SOC crosswalk available on the BLS website to translate the 2000 SOC codes to their corresponding 2010 SOC codes. The concordance table from OES taxonomy to 2000 SOC is available at http://www.workforceinfodb.org/ftp/download/soc2000. Also, the concordance table from the 2000 SOC to 2010 SOC is available at https://www.bls.gov/soc/soccrosswalks.htm

of the knowledge areas that play a significant role in productivity of an industry.[11]

The final step in constructing the LC measure is to compare the composition of the areas of knowledge and their corresponding scores across industries. To this end, we define for each industry i a normalized vector of knowledge scores $\vec{C}_{i,t} = [c_{i,k,t}]_{1\times K}$, and construct LC across each pair of industries by calculating the logarithm of the inverse of the Euclidean distance between their corresponding knowledge score vectors as follows:

$$LC_{i,i',t} = \log\left(\left\|\vec{C}_{i,t} - \vec{C}_{i',t}\right\|^{-1}\right) = -\frac{1}{2}\log\left(\sum_{k=1}^{K}(c_{i,k,t} - c_{i',k,t})^2\right) \tag{3}$$

where $LC_{i,i',t}$ is the labor market connectivity measure between industries i and i' in year t. If two industries rely on completely different sets of knowledge, then those are less likely to rely on the same type of labor, hence not to be fundamentally connected through this channel. Using this method, we construct the labor connectedness measure for each pair of industries in the OES dataset to form a network that consists of industries linked through the labor market with the strength of these linkages being measured by their labor market similarity.

Considering that the labor composition and wages are slow moving variables, we expect the labor market network to be relatively stable and that the labor market connectivity between two industries do not change very rapidly from one year to another. To verify this, for each industry i, we rank all other industries into quintiles based on the value of their LC relative to that industry, i.e., $LC_{i,i',t}$. For each quintile, we then calculate the percentage of these linkages that show up in any of the LC quintiles for industry i three years later. Panel A of Table 1 presents these transition probabilities averaged across all industries over the entire sample.

[Table 1 about here]

[11]For this reason, we present the empirical results using the LC measure constructed based on the labor expenditure throughout the paper. However, our main results are robust to using alternative definitions such as using the occupation-industry level employment as the weights in equation (2).

Consistent with the labor market linkages being persistent across industries and over time, we find that the average likelihood that a linkage transition from the top quintile for an industry to any other quintile over three years is less than 15%. In other words, the similarity between the knowledge composition of industries does not diminish even over a long period of time, suggesting that this connectivity measure is highly persistent cross-sectionally and over time.

Our proposed labor market connectivity measure is constructed using the occupation-level labor expenditure as the weights when averaging the knowledge scores across all occupations in an industry. This could skew our measure towards relatively high-paying occupations that potentially constitute only a fraction of the total labor force in the industry. As a result, it is important to make sure that our results are not driven by the knowledge similarity across the high paying occupations in industry pairs. To this end, we modify this measure by taking the weighted average of knowledge scores across occupations in each industry using the number of employees as the weight. The correlation coefficient between the modified measure, termed $\mathrm{LC}^{emp}_{i,i',t}$, and our benchmark labor connectivity measure is presented in Panel B of Table 1. The estimated correlation coefficient between the two measures is 0.97, suggesting that the cross-sectional dispersion in occupation level wages is unlikely to be a critical determinant of the labor market connectivity across industries.[12]

How is the labor market connectivity measure related to other forms of economic connectivity across firms? This is an important question in light of the existing studies that find cross-predictability between firms that are economically connected through other channels, including input-output relationships (Menzly and Ozbas (2010); Cohen and Frazzini (2008)), physical proximity (Parsons et al. (2020)), and product markets (Hou (2007)). We examine the degree of overlap between our proposed labor market connectivity and other linkages by computing, for each year t, the correlation coefficient between the labor market connectivity

[12] In untabulated results, we also find that our key empirical results hold when we use $\mathrm{LC}^{emp}_{i,i',t}$ as the labor market connectivity measure across industries.

between each pair of firms (i,i') and the following connectivity measures between the same pair of firms: input-output connectivity ($\mathrm{IO}_{i,i',t}$) defined following Menzly and Ozbas (2010) as the average of the percentage sales of firms in industry i that are purchased by firms in industry i' and the percentage purchases made by firms in industry i that are sold by firms in industry i'; and geographical distance (Geo. Distance), defined as the average of the pairwise distance (in miles) between the zip codes of the headquarters of the two firms. The results are reported in Panel B of Table 1. We find that $\mathrm{LC}_{i,i',t}$ has a modest correlation coefficient of 0.27 with $\mathrm{IO}_{i,i',t}$, while it is almost uncorrelated with the geographical distance between firms. In non-tabulated test results, we also find that for an average firm i, another firm i' that belongs to the highest quintile of all industries in terms of $\mathrm{LC}_{i,i',t}$ is in the same sector as i with a probability of only 10.5%.[13] Overall, these results suggest that relative to the existing measures of economic connectivity, our proposed measure of labor market connectivity captures a different form of economic linkage between industries. This, to some extent, alleviates the concern that our results are driven by long established economic linkages. We further confirm this by controlling for the returns of portfolios formed based on these alternative connectedness measures in subsequent analysis.

3 Labor Market Connectivity and Return Predictability

We first examine if labor market linkages – as measured by the similarity in the composition of the type of labor that the industry relies on – can function as conduits for transmission of shocks across industries, through the lens of stock returns. We begin by investigating the role of labor market connectivity in shaping the contemporaneous and predictive relationship between the returns of industries. We conjecture that the knowledge spillover makes industries with overlapping labor types face similar labor-productivity shocks to their connected

[13] We also find that it is in the same state with a 6.99% probability.

industries. Based on this hypothesis, we expect that these productivity shocks would positively spillover across industries that have a strong labor market connection to each other, resulting in a positive relationship with the returns of these industries.

3.1 Portfolio Sorts

To determine whether the returns of the labor market connected industries ($LCIRet_{i,t}$) predict future returns of a subject industry, we sort industries into quintile portfolios at the end of each month based on the value of their $LCIRet_{i,t}$, and compute the average return of each quintile portfolio over the next month. We measure $LCIRet_{i,t}$ for each industry-month by taking average returns of all other industries, weighted by the strength of their connection to the subject industry through the labor market connectivity between industries i and i' ($LC_{i,i',t}$).

$$LCIRet_{i,t} = \frac{\sum_{i' \neq i} LC_{i,i',t-1} \times r_{i',t}}{\sum_{i' \neq i} LC_{i,i',t-1}}, \tag{4}$$

where $r_{i',t}$ is the market cap-weighted (or equally weighted) average return of firms in industry i' in month t.

The summary statistics of industry portfolios sorted by $LCIRet_{i,t}$ are provided in Table 2. Consistent with our hypothesis, we observe a positive relation between the returns of an industry's labor connected industry portfolio and its return in the next month. This relationship is monotonic and economically significant. Specifically, Panel A shows that a portfolio of industries with the highest past $LCIRet$ generates 5.19% higher return compared to the portfolio that consists of industries with the lowest past $LCIRet$ when industry returns are calculated as the value-weighted average returns of their constituent firms. We do not find economically significant difference between the standard deviation of the returns of the two portfolios, and hence it results in a large gap between their Sharpe ratios.

[Table 2 about here]

Panel B examines the predictive power of the LCI portfolio returns when industry returns are constructed using equal-weighted average returns of their constituents. The observed return spread between the high-$LCIRet$ and low-$LCIRet$ is even more pronounced, averaging at 9.23% per year. A potential explanation for this observation is the magnified role of small firms that are known to be subject to sluggish price adjustment when firm returns are equally weighted (Hou (2007)). Small firms are also known to be costlier to arbitrage, largely held by uninformed investors, and receive less investor attention. This is an indication that informational frictions and limits to arbitrage might play an important role in driving the return predictability. We formally test this hypothesis in subsequent section.

Importantly, the spillover of economic shocks through the labor market network can influence firm's policies, which in turn can lead to variations in firm characteristics that are established in the literature to predict equity returns in the cross section. As a result, prior to studying the predictive power of $LCIRet_{i,t}$ for equity returns, it is crucial to examine how this variable relates to such firm characteristics. To this end, we compare $LCIRet_{i,t}$ quintiles in terms of their average constituent firm characteristics for each month as of the most recent June relative to that month. These firm characteristics include size, book-to-market ratio (BM), 12-month momentum, operating leverage, profitability, innovation, investment rate, and hiring rate. A detailed description of these characteristics is provided in the Appendix. Table 3 reports the average values for each quintile portfolio over our sample from 1990 to 2016. Overall, we observe no monotonic relationship between any of these characteristics and $LCIRet$. Among the average characteristics presented in Table 3, we find that "investment" is the only variable in which the long and short legs of the arbitrage portfolio (high-$LCIRet$ vs. low-$LCIRet$) exhibit a statistically significant difference of 0.7% with a t-statistic of 2.67.[14] Moreover, the high-$LCIRet$ quintile has a 12-month momentum that is higher than

[14]Although Table 3 shows a significant link between $LCIRet$ and *investment* at the portfolio level, the direction of this cross-section relation is not economically meaningful. Specifically, *investment* (or asset

that of the low-$LCIRet$ quintile by 0.8% (with a t-statistic of 1.49). Overall, these results imply that the identified cross-sectional predictive power of $LCIRet$ is unlikely to be driven by these characteristics. Nonetheless, in our asset pricing tests, we properly rule out this possibility by including the variables that are suggested to be related to $LCIRet$, or by including their representative factors as control variables.

[Table 3 about here]

Next, we estimate the abnormal returns of each quintile portfolio as well as the arbitrage portfolio that takes a long position in the top 20% $LCIRet$ industries and a short position in the bottom 20% $LCIRet$ industries with respect to a number of factor models, including the capital asset pricing model (CAPM) with the market (MKT) factor, the three-factor model (FF3) of Fama and French (1993) with the MKT, size (SMB), and book-to-market (HML) factors, the four-factor model (FFC4) of Fama and French (1993) and Carhart (1997) with the MKT, SMB, HML, and momentum (MOM) factors, the five-factor model (FF5) of Fama and French (2015) with the MKT, SMB, HML, investment (CMA), and profitability (RMW) factors, the q-factor model (HXZ4) of Hou et al. (2015) with the MKT, size (SMB_Q), investment ($R_{I/A}$), and profitability (R_{ROE}) factors, the mispricing factor model (SY4) of Stambaugh and Yuan (2017) with the MKT, SMB, management (MGMT), and performance (PERF) factors, the behavioral factor model (DHS3) of Daniel et al. (2020) with the MKT, post-earnings-announcement drift (PEAD), and financing (FIN) factors, and the seven-factor model (FFCPS7) of Fama and French (2015), Carhart (1997), and Pastor and Stambaugh (2003) with the MKT, SMB, HML, CMA, RMW, MOM, and the liquidity risk (LIQ) factors. Controlling for these risk, mispricing, and behavioral factors helps to ensure that the labor market connectivity indeed contains incremental predictive power beyond these well-known factor models.[15]

growth) has been shown in the literature to predict future stock returns negatively, while $LCIRet$ positively predicts future stock and industry returns.

[15] We also control for the well-known industry return predictors using 5x5 bivariate portfolios. Specifically,

Table 4 summarizes the abnormal returns for each portfolio and for the portfolio that is long the quintile with the highest *LCIRet* and short the quintile with the lowest *LCIRet*. Consistent with our previous observations, the abnormal returns (alphas) of the *LCIRet*-sorted portfolios indicate a positive relation between *LCIRet* and future stock performance across all factor models. Specifically, as reported in Panel A of Table 4, firms in the high-*LCIRet* (low-*LCIRet*) quintile earn the highest (lowest) abnormal return, yielding an annual abnormal return spread that ranges from 3.53% using Stambaugh and Yuan (2017)'s mispricing factor model to 5.53% (5.38%) using the three (five) factor model of Fama and French (2015). A similar pattern is observed in Panel B, where industry portfolio returns are constructed using equal-weighted stock returns. Also, consistent with our results in Table 2, we find more pronounced abnormal returns to the equal-weighted long-short portfolio of *LCIRet*-sorted industries, with an alpha ranging from 7.13% to 9.86% per year.

Another notable point in Table 4 is that controlling for various risk factors does not change the magnitude and statistical significance of the return spreads on the *LCIRet*-sorted portfolios for most of the factor models.[16] The exceptions are the alphas of the long-short portfolio under the mispricing factor models, where the alpha in Panel A decreases from 5.48% (per annum) for the CAPM model to 3.53% for SY4 model and 3.93% for DHS3 model and the corresponding t-statistic decreases from 3.23 to 1.60 and 1.82, respectively. This evidence suggests that the return predictability is potentially driven by mispricing rather than compensation for risk.

[Table 4 about here]

for each month, we first sort industries into quintile portfolios based on a control variable. Then, we further sort industries by the lagged returns of labor market connected industries ($LCIRet_{i,t-1}$) into quintile portfolios within each control variable quintile. Table A1 in the Appendix shows that after controlling for the lagged return of industry i ($\text{Ret}_{i,t-1}$), the return of industry i between $t-12$ and $t-2$ ($\text{Ret}_{i,t-12:t-2}$), the lagged returns of its supplier and customer connected industries ($\text{IORet}_{i,t-1}$), and the lagged return of the broader industry group of industry i ($\text{RetSIC2}_{i,t-1}$), the predictive relation between industry returns and the past returns of their labor-market-connected neighboring industries remains positive and highly significant.

[16] The t-statistics reported in our tables are Newey and West (1987) adjusted with optimal number of lags according to Newey and West (1994) to control for heteroskedasticity and autocorrelation.

Turning to factor loadings presented in Panel C to Panel F of Table 4, we find that the high-minus-low value-weighted portfolio returns have significantly positive loadings on $PERF$ factor of SY4 model and $PEAD$ factor of DHS3 model, while having statistically insignificant loadings for all other factors considered in the paper. On one hand, $PERF$ factor is based on the cluster of multiple anomalies that reflect mispricing related to performance. On the other hand, $PEAD$ factor is based on the eponymous post-earnings-announcement drift (PEAD) phenomenon, motivated by the theory that limited investor attention induces stock market underreaction to new information. Therefore, the reduction in alphas mainly originates from the $LCIRet$-sorted portfolios' exposure to the mispricing factors associated with short horizon underreaction. Moreover, we find that the industry exposures to those two factors are significantly concentrated in short-leg of the arbitrage portfolios. This result is consistent with the arbitrage asymmetry phenomenon noted in Stambaugh and Yuan (2017), which leaves more uncorrected overpricing than uncorrected underpricing owing to short-sale constraints.

The construction of the arbitrage portfolio in Table 4 is in line with the methodology adopted by Moskowitz and Grinblatt (1999), where investment positions are taken on *industry portfolios* that belong to the highest and lowest quintiles based on their lagged $LCIRet$. In Table A4 of the Appendix, we employ the factor construction methodology used by Fama and French (1993, 2015) to investigate if the observed performance extends to portfolios of firms that are adjusted for size, which is known to predict average returns at the firm level. Specifically, we repeat the tests in Table 4 by constructing 2x3 value-weighted bivariate portfolios using firm-level data, where the 2x3 double-sorted portfolios are constructed by first allocating stocks to two size groups (Small and Big) at the end of each month, and then stocks in each size groups into three $LCIRet$ groups (Low, Mid, and High) based on the lagged returns of labor market connected industries. The consequential 2x3 high-low factor is the average of the two high-low value-weighted portfolio returns in each size groups as in Fama and French (1993, 2015).

Panel A of Table A4 shows that the average return on the labor market network (LMN) driven *stock*-momentum factor, denoted by MOM^{stock}_{LMN}, is economically large and statistically significant; 7.04% per annum with a t-statistic of 3.17. We also construct a similar, labor market network driven *industry*-momentum factor, MOM^{ind}_{LMN}, based on the 2x3 value-weighted bivariate portfolios of industry size and $LCIRet$ using industry-level data. As presented in Panel B of Table A4, the average return on this newly proposed industry-momentum factor is again economically and statistically significant; 4.35% per annum with a t-statistic of 3.27. Finally, we investigate whether long-established momentum factors explain the LMN driven *stock*-momentum and/or *industry*-momentum factors. Table A4 demonstrate that the CAPM alphas on both MOM^{stock}_{LMN} and MOM^{ind}_{LMN} factors are highly significant; 7.65% per annum (t-stat.=3.80) and 4.88% per annum (t-stat.=3.81), respectively. Table A4 also shows that the alphas on both MOM^{stock}_{LMN} and MOM^{ind}_{LMN} factors remain strong after controlling for the established stock, industry, and customer momentum factors of Carhart (1997), Moskowitz and Grinblatt (1999), and Menzly and Ozbas (2010), indicating that the labor market network that connects the labor force across different industries plays an important role in generating a strong labor momentum effect, which is distinct from the existing, long-standing momentum phenomena.

Overall, the above results point to a mispricing/behavioral interpretation of the identified abnormal returns, resulting from investors' underreaction to news about the labor market-linked peers. We further rule out that the results are explained by the portfolio exposures to various macroeconomic shocks in a generalized method of moments (GMM) framework using a two-factor model with the following empirical stochastic discount factor:

$$M_t = 1 - b_M \times MKT_t - b_F \times F_t, \tag{5}$$

where MKT_t is the market factor and F_t is a proxy for the second aggregate shock using the first difference (Δ) in one of the following aggregate variables in year t: a proxy for aggregate labor adjustment costs – the cross-sectional standard deviation of firm level hiring rate ($STDHN$), investment specific shocks ($iSHOCK$), aggregate labor market tightness (LMT), one component of capital reallocation shock – sales of property, plant and equipment ($SPPE$), another component of capital reallocation shock – mergers and acquisitions (AQC), and the aggregate capital reallocation shock – the sum of sales of property, plant and equipment and mergers and acquisitions ($SPPEAQC$). The test assets include the five value-weighted portfolios of industries sorted by $LCIRet_{i,t}$.

In other words, we estimate the risk factor loadings on the two aggregate shocks based on the asset pricing moment condition $E[r^e_{i,t} \times M_t] = 0$, which can also be written as

$$E[r^e_{i,t}] = \alpha_i + b_M Cov(MKT_t, r^e_{i,t}) + b_F Cov(F_t, r^e_{i,t}), \tag{6}$$

where $r^e_{i,t}$ is the excess return on test asset i in year t, α_i is the pricing error associated with test asset i, and b_M and b_F are the loadings on the covariances of $r^e_{i,t}$ with the excess market return (MKT_t) and the risk factor (F_t), respectively.

[Table 5 about here]

Table 5 reports the pricing error for each macroeconomic shock listed above and each test asset. We find that the pricing errors associated with the fourth and fifth $LCIRet$ quitiles are positive and significant across all specifications for the pricing kernel. More importantly, this is also the case for the high- minus low-$LCIRet$ portfolio, indicating that the observed return spread is likely not priced by these aggregate shocks. Consistent with these findings, we find that the validity of the asset pricing moment condition is rejected based on the estimated J-Statistics.[17] Overall, the results in Table 5 show that the observed

[17]The J-statistic, originally introduced by Sargan (1958) and then extended by Hansen (1982) in a GMM framework, is based on the assumption that model parameters are identified via a priori restrictions on the coefficients, and tests the validity of over-identifying restrictions. Under the null hypothesis that the over-identifying restrictions are valid, the J-statistic is asymptotically distributed as a chi-square variable with (m–k) degrees of freedom, where m is the number of instruments and k is the number of endogenous variables.

return spread on $LCIRet$-sorted portfolios is unlikely due to a risk premium implied by the above macroeconomic shocks.

The above observations are helpful in understanding whether the observed return spread is driven by variations in industry exposures to the risk factors, for which we find very limited support. However, a possible alternative explanation for the observed return spread is based on the industry characteristics that are correlated with the exposures to unobserved risk factors. To the extent that these characteristics are persistent and are common across labor market linked industries, we may still observe return predictability across industries with high LC. In other words, the observed return spread could be due to a risk premium associated with the common exposure of an industry and its linked industry to a persistent priced risks. Figure 1 shows the transition of industries across $LCIRet$ quintiles over various horizons. Specifically, at the beginning of each month we give a score to each industry based on the quintile that it belongs to (5 for the highest quintile, 1 for the lowest quintile). We then keep track of these scores for the same industries over time and measure the average value of those scores for industries that initially belonged to each quintile. A persistent $LCIRet$ implies that industries should remain in the same quintile over a relatively long period of time. In contrast, Figure 1 shows that the industries transition from each quintile to any other quintile with almost the same probability. This suggests that $LCIRet$ being driven by a persistent industry characteristic is unlikely.

[Figure 1 about here]

3.2 Persistence of the Returns Over Time

The portfolio sort results indicate that the returns of an industry are crucially determined by the past returns of its labor connected industries. We now evaluate whether this relation persists over time. Specifically, we compare the excess return of the portfolio of industries that belong to the high-$LCIRet$ quintile with those in the low-$LCIRet$ quintile. To this end, we plot the time series of cumulative returns of the high-minus-low $LCIRet$-sorted portfolios over the period from January 1991 to April 2017. For comparison, we also plot the time series of cumulative returns of the SMB (small-minus-big stocks), HML (high-minus-low book-to-market stocks), RMW (robust-minus-weak operating profitability stocks), and CMA (low-minus-high investment firms) factors. All factor returns are constructed using value-weighted univariate sorts on those firm characteristics and the data are obtained from Kenneth French's online data library. Figure 2 shows that the time-series variation of the high-minus-low $LCIRet$-sorted portfolio returns are not correlated with any other factor returns and outperform those factors over the sample period 1991-2017.

[Figure 2 about here]

3.3 Fama-MacBeth Regressions

The results in the previous section support the existence of a strong and positive relationship between the returns of labor market linked industries. In this section, we investigate if the identified cross-industry return predictability is driven by other economic linkages across industries that are known to generate predictability across industries. Specifically, we consider input-output linkages between industries as an alternative conduit for transmission of shocks, which have been shown to generate return predictability across linked industries (Menzly and Ozbas (2010); Cohen and Frazzini (2008)). Moreover, Hou (2007) provides evidence for the information clustering at the product market level as the reason for a lead-lag effect that has been identified by Lo and MacKinlay (1990) to exist across firms with different sizes. As a result, it is important to distinguish the labor market connectivity channel from these alternative channels which have been shown to induce return predictability.

We perform monthly Fama and MacBeth (1973) regressions of the form:

$$Ret_{i,t} = \beta_t^0 + \beta_t^1 \cdot LCIRet_{i,t-1} + \sum_{k=1}^{K} \beta_t^j \cdot X_{i,t-1}^k + \eta_{i,t}, \quad i = 1, \cdots, N_t \tag{7}$$

where $Ret_{i,t}$ is the return of industry i in month t, and $LCIRet_{i,t-1}$ and $X_{i,t-1}^k$ are the return to industry i's LCI portfolio and the k-th control variable at the end of month $t-1$. As control variables, we first include the one-month lagged return of industry i to account for a possible short-term reversal effect as well as its return between $t-12$ and $t-2$ to control for a possible momentum effect. Second, we include the lagged return of the portfolio industries that belong to the broader industry group of industry i, defined by 2-digit SIC codes for years prior to 1997 and 3-digit NAICS code from 1997 onward. This would help us to examine the possibility that the observed return predictability between labor market linked industries is driven by the lead-lag effect that is manifested among industries that share the same broad product market. Third, for each industry, we construct a portfolio composed of its supplier and customer industries based on the data from the Bureau of Economic Analysis (BEA) input-output (IO) accounts. We calculate the monthly returns for this portfolio using the share of the average of the industry's total purchase and total sales to each industry as weights.[18] We then include the lagged return of this portfolio as a control variable to test if the input-output relationships explain the observed relationship between the $LCIRet$ for an industry and its future returns. Finally, we consider the (intra-industry) value-weighted average of the number of analysts, the percentage of institutional ownership, the log of market capitalization, the book-to-market ratio, the change in total assets, and the gross profitability.

[Table 6 about here]

The summary of the results from the Fama-MacBeth regressions are reported in Table 6. Throughout all specifications, the coefficient associated with the lagged value of $LCIRet$

[18] The readers can refer to Sharifkhani and Simutin (2021) for more information about the data and methodology adopted in calculating these portfolio returns.

remains positive and significant. This suggests that the labor market connectivity across industries is an important channel for transmission of economic shocks across industries. This channel functions in parallel with the input-output linkages as well as those resulting from overlaps in industry's product markets.[19]

3.4 The Role of Informed Trading and Limits to Arbitrage

Hong and Stein (1999) propose a theoretical model in which gradual diffusion of information among investors explains the observed predictability of stock returns. In their model, at least some investors can process only a subset of publicly available information because either they have limited information-processing capabilities or searching over all possible forecasting models using publicly available information itself is costly (Hirshleifer and Teoh (2003)), and there are limits to arbitrage (Shleifer and Vishny (1997)). Due to investors' limited attention and costly arbitrage, new informative signals are incorporated into stock prices partially because at least some investors do not adjust their demand by recovering informative signals from firm fundamentals or observed prices. As a result of this failure on the part of some investors, stock returns exhibit predictability.

Our findings suggest that stocks that are economically related through the labor market cross-predict each other's returns. We investigate whether the results vary to the extent in which the information is supplied to the market and draw attention from market participants. As implied by limited-information models, the slow diffusion of information and the resulting cross-predictability between economically related assets is more pronounced when investors are less informed. Menzly and Ozbas (2010) examine the role of informed trading as a determinant of the cross-predictability between economically related customer and supplier

[19] Table A2 in the appendix confirms these results using the firm-level Fama-MacBeth regressions instead of the industry level regressions employed in Table 6. In those firm-level regressions, we also consider additional control variables including the firm level short-term reversal, momentum, long-term reversal, size, book-to-market, investment, gross profitability as well as the industry level reversal, momentum, and customer-supplier return.

industries and find a negative relationship between their proxies of informed investment and the magnitude of cross-predictability. They argue that information is incorporated into the prices much faster in the presence of many informed investors, and this leaves little room for cross-predictability. In other words, when investors are more informed and less likely to suffer limited attention bias, information – as gauged by the movements in asset prices – diffuses faster. This has important implications for our results. The main hypothesis of this paper attributes the cross-industry return predictability to the spillover of labor productivity shocks along labor force linkages and the slow information diffusion of the shocks. Hence, a natural prediction is that cross-industry return predictability should be negatively related to the level of information that is available in the market. The corresponding test is to examine the interaction between the strength of labor market linkages and variables that proxy for the amount of information available to the market. Following Nagel (2005) and Menzly and Ozbas (2010), we adopt the level of analyst coverage and the level of institutional ownership as proxies for informed trading.[20]

To examine the extent to which the observed return predictability is affected by the level of informed trading, we split industries into two subsamples based on proxies for the presence of informed investors. Specifically, at the end of each month, we construct two portfolios: one that consists of industries with the intra-industry value-weighted average number of analysts (percentage of institutional holdings) above the median level, and one that includes industries with below the median level across industries. We then compare the results of Fama-MacBeth regressions in which the dependent variable is the return of a portfolio with above median (high) level of informed investors with the results of a regression with the dependent variable being the return of a portfolio with below median (low) level of informed investors.

[20]The level of analyst coverage at the industry level is constructed based on the number of analysts with earnings-per-share forecasts from the I/B/E/S detail detail history file. The level of institutional ownership is measured by the fraction of total shares outstanding that are owned by institutional investors as reported in Thompson-Reuters' Institutional Holdings (13F) database.

[Table 7 about here]

We report our results for the informed investor proxies in Table 7. Panel A reports the results for analyst coverage, while Panel B shows the results for institutional holdings. Regardless of the proxy used for informed trading, we find that stocks with lower ownership of informed investors exhibit more cross-predictability compared to stocks with higher ownership of informed investors. The diff-and-diff analysis of the slope coefficients on the lagged $LCIRet$ for industries with high vs. low analyst coverage and institutional ownership also generates an economically and statistically significant difference. These results are consistent with the idea that stocks with more informed trading adjust more quickly to the relevant information originating from labor market connected industries.

We also expect that the cross-predictability is stronger among stocks with more binding arbitrage costs since arbitrageurs' demand for a stock is inversely related to its arbitrage cost. To test this prediction, we follow Pontiff (2006) and use idiosyncratic volatility as a proxy for costly arbitrage. Specifically, we rely on Ang, Hodrick, Xing, and Zhang (2006) and estimate the monthly idiosyncratic volatility as the standard deviation of the daily residuals from the regression of daily excess stock returns on the three factors of Fama and French (1993) over the past one month. Then, we split industries into two portfolios based on the average idiosyncratic volatility. Panel C reports that the slope coefficient on the lagged $LCIRet$ for high volatility industries is economically and statistically greater than the corresponding slope coefficient for low volatility industries; i.e., the difference in the coefficient estimates on $LCIRet$ for industries with high and low idiosyncratic volatility is positive and statistically significant. This result lends support to our prediction that the cross-predictability is stronger for stocks that are costlier to arbitrage and hence arbitrage risk also contributes to the lagged response.

4 The Economic Channel

The reported results confirm that the returns of labor market connected industries have an economically and statistically significant predictive power for an industry's future equity returns. Importantly, this predictive power is not explained by the input-output linkages or overlapping product market across industries. In this section, we further investigate the underlying channel through which these labor market linkages can induce a positive cross-sectional correlation between stock returns.

4.1 Spillover Effects in Fundamentals

The first question that we address in this section is related to our proposed hypothesis that the linkages between industries through the labor market would give way to positive spillover of labor productivity shocks across industries with overlapping required areas of knowledge. Contrary to this positive productivity spillover channel, the productivity shock also has potential to negatively affect labor market connected industries to the extent that industries with overlapping types of labor are competing for labor in the same segments of the labor market. While the empirical evidence presented in previous sections of the positive predictive relationship among labor connected industries suggests that the positive productivity spillover channel perhaps dominates the competition channel, it is prudent to check that the same relationship holds between firm fundamentals across labor market connected industries.

Is there a positive spillover of labor productivity across industries that are linked through the labor market? We address this question by exploring the relationship between labor expenditure across industries and make a contrast between industry pairs that have a strong labor market connection with those with a weaker connection. To this end, we run the following panel regressions:

$$\Delta V_{i,y} = \beta_0 + \beta_1 \cdot \text{LCIRet}_{i,y-1} + \beta_2 \cdot \Delta V_{i,y-1} + \beta_3 \cdot Controls_{i,y-1} + \lambda_y + \epsilon_{i,y} \quad (8)$$

$$\Delta V_{i,y} = \beta_0 + \beta_1 \cdot \text{LCI-}V_{i,y-1} + \beta_2 \cdot \Delta V_{i,y-1} + \beta_3 \cdot Controls_{i,y-1} + \lambda_y + \epsilon_{i,y} \quad (9)$$

where $V_{i,y}$ is one of the labor-related variables that captures cross-effect of labor productivity shocks across industries: (i) $Wage_{i,y}$ is the employment-weighted average of the hourly wages across all occupations in industry i in year y, (ii) $LaborExp_{i,y}$ is the total labor costs for industry i in year y, defined as the product of the employment and the associated wage in each occupation in industry i, aggregated across occupations in that industry, and (iii) $Empl_{i,y}$ is the total employment in industry i in year y. We measure LCI-$V_{i,y-1}$ for each industry-year by taking average of labor-related variables of all other industries, weighted by the strength of their connection to the subject industry through the labor market connectivity between industries i and i' ($LC_{i,i',y}$): LCI-$V_{i,y} = \frac{\sum_{i' \neq i} LC_{i,i',y-1} \times \Delta V_{i',y}}{\sum_{i' \neq i} LC_{i,i',y-1}}$.

Our coefficient of interest is β_1, which captures the effect of labor market linkages on the lead-lag relationship between these labor-related variables. Throughout this test, we control for the product market effect as well as the supplier and customer effects, where the common product market is defined as the broader industry group of industry i (2-digit SIC and 3-digit NAICS) and the supplier and customer industries based on the data from the BEA's input-output (IO) accounts. By doing so, we address the possibility that observed lead-lag relationships between these variables are driven by either persistent product market level demand shocks that affect both industries at different times or the delayed response of fundamental shocks through the supplier-customer network. We include the year fixed-effect and standard errors are clustered by year and industry.

[Table 8 about here]

Models (1) and (2) in each panel of Table 8 suggest that $LCIRet$ has a strong predictability in the future growth rate of wage, labor expenditure, and employment of the focal industry. Beyond the predictability that originates from industry portfolio returns, in Model (3) and (4) of Panel A, we find that there is also a positive lead-lag relationship between changes in the wages of labor market connected industries, which is explained neither by persistent shocks to the industries nor the supplier and customer network spillover. To the extent that wage growths capture shocks to the labor productivity, we can interpret this result as evidence for positive spillover of labor productivity across linked industries. We also observe a similar pattern in the labor expenditure in Panel B, suggesting that firms in the linked industry are unlikely to react to this positive wage spillover by reducing the labor hours. We can directly see this in Panel C where we include the changes in the number of employees as the labor related variable. In fact, as evidenced by the positive and significant coefficient β_1, an increase in the labor force by a connected industry would result in a differentially more positive change in the employment in the labor market connected industry.

While wage and labor expenditure growths are positively associated with changes in the labor productivity, those are not direct measures of it. We, therefore, come up with empirical proxies that provide more accurate characterization of the labor productivity in each industry. Our first proxy is the growth rate of sales per employee. To construct this variable, we calculate the ratio of sales to the number of employees for each firm gathered from Compustat and then convert those ratios to an industry-level aggregate by taking the value-weighted average of the constituents within a focal industry. Our second measure is the rate at which labor is used to produce output of goods and services, expressed as output per hour of labor and sourced from the Bureau of Labor Statistics.

To test the hypothesis of the labor productivity spillover through the labor market connected industries, we run the following panel regressions in Table 9:

$$\Delta LP_{i,y} = \beta_0 + \beta_1 \cdot \text{LCIRet}_{i,y-1} + \beta_2 \cdot \Delta LP_{i,y-1} + \beta_3 \cdot Controls_{i,y-1} + \lambda_y + \epsilon_{i,y} \quad (10)$$

$$\Delta LP_{i,y} = \beta_0 + \beta_1 \cdot \text{LCI-LP}_{i,y-1} + \beta_2 \cdot \Delta LP_{i,y-1} + \beta_3 \cdot Controls_{i,y-1} + \lambda_y + \epsilon_{i,y} \quad (11)$$

where $\Delta LP_{i,y}$ is a measure of labor productivity growth of industry i in year y. We present the results for the annual growth rate of sales per employee in Panel A and that for the output per hour of labor in Panel B. Similarly to other LCI-variables in Table 8, we measure LCI-LP$_{i,y-1}$ for each industry-year by taking the average of labor productivity growth rates of all other industries, weighted by the strength of their connection to the subject industry through the labor market connectivity between industries i and i' ($LC_{i,i',y}$): LCI-LP$_{i,y}$ = $\frac{\sum_{i' \neq i} LC_{i,i',y-1} \times \Delta LP_{i',y}}{\sum_{i' \neq i} LC_{i,i',y-1}}$.

[Table 9 about here]

Throughout all specifications, the coefficients associated with the lagged values of both LCIRet and LCI-LP are positive and significant, indicating that there is direct evidence of positive spillover of labor productivity across labor market linked industries. Contrary to this evidence, Table A3 in the Appendix shows that LCIRet does not have strong predictability for capital productivity growth or intermediate purchase productivity growth, highlighting the unique role of labor productivity spillover mechanism behind the return predictability.

Similarly to the labor productivity spillover, we examine the relationship between the profitability of labor market connected industries by running the following panel regressions:

$$\Delta Prof_{i,y} = \beta_0 + \beta_1 \cdot \text{LCIRet}_{i,y-1} + \beta_2 \cdot \Delta Prof_{i,y-1} + \beta_3 \cdot Controls_{i,y-1} + \lambda_y + \epsilon_{i,y} \quad (12)$$

$$\Delta Prof_{i,y} = \beta_0 + \beta_1 \cdot \text{LCI-}y_{i,y-1} + \beta_2 \cdot \Delta Prof_{i,y-1} + \beta_3 \cdot Controls_{i,y-1} + \lambda_y + \epsilon_{i,y} \quad (13)$$

where $\Delta Prof_{i,y}$ is the percent change in the profitability for industry i in year y. The industry-level profitability is calculated as the sum of the total revenue (REVT) minus cost of goods sold (COGS) divided by the sum of total assets (AT), following Novy-Marx (2013). We measure LCI-$Prof_{i,y-1}$ for each industry-year by calculating the average of profitability growth rates of all other industries, weighted by the strength of their connection to the subject industry through the labor market connectivity between industries i and i' ($LC_{i,i',t}$): LCI-$Prof_{i,y} = \frac{\sum_{i' \neq i} LC_{i,i',y-1} \times \Delta Prof_{i',y}}{\sum_{i' \neq i} LC_{i,i',y-1}}$. Our coefficient of interest is β_1, which represents the impact of labor market linkages on the correlation between the profitability of industries.

[Table 10 about here]

The results are reported in Table 10. Throughout all specifications, we observe a positive and significant relationship between the changes in the profitability of an industry and the lagged changes in the profitability of another industry when the two industries have a relatively strong labor market connectivity, implying that a positive productivity shock can affect a linked industry over the next year. This highlights the important role of labor market linkages in transmission of productivity shocks across industries.

Lastly, to provide more direct evidence to substantiate the hypothesis that the return predictability is driven by the positive spillover of labor productivity shocks along the labor network, we use the above mentioned LCI-LP to predict stock returns. Specifically, we perform monthly Fama and MacBeth (1973) regressions of the form:

$$Ret_{i,t} = \beta_t^0 + \beta_t^1 \cdot \text{LCI-LP}_{i,lagged} + \sum_{k=1}^{K} \beta_t^j \cdot X_{i,t-1}^k + \eta_{i,t}, \quad i = 1, \cdots, N_t \tag{14}$$

where $Ret_{i,t}$ is the return of industry i in month t, and $X_{i,t-1}^k$ is the k-th control variable at the end of month $t-1$. The results are reported in Table 11. As in Table 9, we use the annual growth rate of sales per employee in Panel A and that of output per hour of labor sourced from Bureau of Labor Statistics in Panel B of Table 11 as a measure of labor productivity growth of industry i in year y ($\Delta LP_{i,y}$). For LCI-LP$_{i,lagged}$, we first construct

LCI-LP$_{i,y}$ for each industry-year by taking average of labor productivity growth rates of all other industries and then lag LCI-LP$_{i,y}$ by a minimum of 4-months to ensure the availability of financial and macroeconomic data to investors. We find that the coefficients associated with the lagged value of LCI-LP are positive and significant for all specifications. This finding provides direct supporting evidence to the impact of labor productivity shock transmission through the labor market network on asset prices.

[Table 11 about here]

Overall, the results are consistent with the hypothesis that the return predictability between labor market connected industries is driven by the positive spillover of labor productivity shocks along these links.

4.2 Labor Productivity Spillover and Adoption Capacity

Our findings so far suggest that the identified cross-industry return predictability is driven by frictions in information markets that makes labor productivity shocks to be impounded into the prices of labor market connected industries with a delay. An important question which follows from this hypothesis is whether we observe a more pronounced effect when an industry is better equipped to take advantage of the productivity shock in its linked industries.

Our hypothesis suggests that if a firm has the required resources to enhance its labor productivity, we should observe a greater price reaction to labor productivity shocks from its labor market connected industries. In other words, the return spread between firms with higher past LCI portfolio returns and those with lower LCI portfolio returns should be higher among firms that have a greater capacity to take advantage of labor productivity shocks. This is exactly what we find empirically. Specifically, Table 12 shows that the coefficient for $LCIRet_{i,t-1}$ is as large as 0.720 (t-stat = 2.79) when the the firms in the subject industry portfolio have been in the upper half of all industries in terms of innovations, proxied by the citation-weighted value of the firm's patents based on the method proposed by Kogan, Papanikolaou, Seru, and Stoffman (2017).[21] In comparison, for an industry portfolio with firms that are below median in their innovations, the same coefficient is only 0.315 (t-stat = 2.01), producing a difference of 0.405 (t-stat = 1.92) between the two sub-samples.

[Table 12 about here]

This difference between the regression coefficients for the LCI portfolio return is even higher when firms are splitted into sub-samples based on their gross profitability. In particular, when the industry portfolio is constructed based on firms in the upper half of industries in terms of profitability, the resulting coefficient associated with the predictive variable $LCIRet_{i,t-1}$ is equal to 0.523 (t-stat = 3.20) for firms in high-profitability industries, compared to 0.063 (t-stat = 0.43) for firms in low-profitability industries, giving a statistically significant difference of 0.460 (t-stat = 2.43) between the two sub-samples.

Finally, we compare the predictive power of the lagged returns of connected industries for industries with different levels of overall labor mobility. Donangelo (2014) defines labor mobility as the industry's average reliance on occupations that are most common across all industries. To the extent that there is complementarity between occupations in an industry, an industry with a higher labor mobility would find it easier to acquire its desired labor in response to positive labor productivity shocks. In other words, the overall labor adjustment costs faced by a high-labor mobility industry would be lower than the costs for a low-labor mobility industry. Thus, we conjecture that there would be a stronger predictability associated with lagged returns of labor connected industries for industries with higher labor mobility. The results reported in the last three columns of Table 12 are consistent with this conjecture: we observe a difference of as much as 0.507 (t-stat = 2.16) between the two coefficients associated with $LCIRet_{i,t-1}$ of the above-median labor mobility industries and

[21] The data are downloaded from Amit Seru's website.

below-median labor mobility industries.

Overall, these results suggest that a firm's capacity to benefit from labor productivity enhancing shocks is an important determinant of the predictive power of the lagged returns of the labor market connected industries.

5 Conclusion

This paper introduces a novel measure of labor network that captures how closely two industries are connected in the labor market. Our measure of labor market connectivity focuses on the closeness of the job knowledge composition of the labor forces in industry pairs. Through the lens of stock returns and real quantities, we find a positive spillover effect when productivity shocks transmit through the labor market, which dominates the potential negative effect that could arise due to competition in the labor market.

The economic magnitude of the effect is not trivial. We find that a portfolio of value-weighted industry returns whose LCI past returns are in the top quintile outperform those with LCI past returns in the bottom quintile by 5% per year. This return spread is not explained by leading empirical asset pricing models. Further analyses indicate that the return predictability cannot be explained by these portfolios' exposures to several macroeconomic shocks and is more likely due to informational frictions and limits-to-arbitrage.

Our analyses on the real quantities aid in understanding the economic underpinnings of the observed return predictability. We find that a focal industry's labor policies (wage growth, employment growth, and labor expenses growth), labor productivity growth, profitability growth all experience a positive spillover effect from their LCI's corresponding quantities with a lag. Overall, our paper suggests that the labor market network plays an important role in knowledge and labor productivity shock spillover.

Appendix

The firm-level characteristics used in our empirical analysis are based on accounting data from Compustat, and are defined as follows:

• Size is the natural logarithm of the firm's market capitalization.

• Book-to-Market (BM) is the natural logarithm of the firm's book value to market equity, following Fama and French (1992).

• Operating Leverage (Op. Lev.) is defined as selling, general and administrative expense (XSGA) plus the cost of goods sold (COGS), divided by the total assets (AT).

• Investment to Capital ratio (IK) is defined as capital expenditures (CAPX) divided by the net property, plant, and equipment (PPENT).

• Market Leverage (MktLev) is the ratio of total debt to market value of firm, following Fan, Titman, and Twite (2012). Total debt is the sum of the long-term interest bearing debt (DLTT) and the book value of short-term debt (DLC). Market value of firm is defined as the market value of common equity as defined in Fama and French (1992), plus the book value of preferred stock (PSTK) and the total debt.

• Free Cash Flow (FCF) is defined following Novy-Marx (2013) as the firm's free cash flow to book equity. Free cash flow is the total of net income (NI) and depreciation and amortization (DP) minus capital expenditure (CAPX) and changes in working capital (WCAPCH).

• Profitability (Prof) is also defined following Novy-Marx (2013) as the total revenue (REVT) minus cost of goods sold (COGS) divided by total assets (AT).

• Hiring Rate (HN) is defined following Belo et al. (2014) as the ratio of one year change in total number of employees (EMP) in year t divided by the average number of employees in year t and year t 1.

• Innovation (Innov) is proxied by the citation-weighted value of the firm's patents based on the method proposed by Kogan et al. (2017). The data is downloaded from Amit Seru's website

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Table 1: Summary Statistics of Labor Market Connectivity

This table presents summary statistics of the labor market connectivity, defined between each industry pair (i, i') as

$$LC_{i,i',t} = -\frac{1}{2}\log\left(\sum_{k=1}^{K}(c_{i,k,t} - c_{i',k,t})^2\right)$$

where $\vec{C}_{i,t} = [c_{i,k,t}]_{1\times K}$ is a normalized vector of knowledge score. For each industry i, quintile portfolios are formed by ranking every other industry i' based on the value of the labor market connectivity between the industry pair, i.e., $LC_{i,i',t}$. Panel A reports the transition probabilities of the pairwise labor market connectivity, calculated as the percentage of linkages in a quintile (row) in year t that falls in any quintile (column) in year $t+3$. The probabilities are averaged across all industries over the period between 1990 and 2016. Panel B presents the correlation between $LC_{i,i',t}$ and the following alternative connectivity measures: employment-weighted labor market connectivity ($\mathrm{LC}^{emp}_{i,i',t}$); input-output connectivity ($\mathrm{IO}_{i,i',t}$) defined as the average of the percentage sales of firms in industry i that are purchased by firms in industry i' and the percentage purchases made by firms in industry i that are sold by firms in industry i'; and geographical distance (Geo. Distance), defined as the average of the pairwise distance (in miles) between the zip codes of the headquarters of the firms in the two industries. The pair-wise correlation coefficients are calculated for each year, and is averaged across all years between 1990 and 2016.

Panel A: Transition Probabilities

	1	2	3	4	5
1	86.86%	11.69%	1.18%	0.22%	0.04%
2	10.99%	72.23%	14.92%	1.59%	0.26%
3	1.74%	14.16%	69.14%	13.72%	1.25%
4	0.40%	1.77%	13.40%	72.11%	12.32%
5	0.10%	0.34%	1.34%	12.20%	86.02%

Panel B: Correlation with Other Linkages

	$\mathrm{LC}_{i,i',t}$	$\mathrm{LC}^{emp}_{i,i',t}$	$\mathrm{IO}_{i,i',t}$	Geo. Distance
$\mathrm{LC}_{i,i',t}$	1.000			
$\mathrm{LC}^{emp}_{i,i',t}$	0.971	1.000		
$\mathrm{IO}_{i,i',t}$	0.272	0.243	1.000	
Geo. Distance	0.022	0.023	-0.001	1.000

Table 2: Univariate Portfolios of Industries Sorted by Labor Market Connectedness

This table presents the summary statistics of the value-weighted (Panel A) and equal-weighted (Panel B) returns of industry portfolios sorted by the lagged returns of labor market connected industries ($LCIRet_{i,t}$). We measure $LCIRet_{i,t}$ for each industry-month by taking the average returns of all other industries, weighted by the strength of their connection to the subject industry through the labor market connectivity between industries i and i' ($LC_{i,i',t}$). We denote $LC_{i,i',t}$ and $LCIRet_{i,t}$ as

$$\begin{aligned} LC_{i,i',t} &= -\frac{1}{2}\log\left(\sum_{k=1}^{K}(c_{i,k,t}-c_{i',k,t})^2\right) \\ LCIRet_{i,t} &= \frac{\sum_{i'\neq i} LC_{i,i',t-1}\times r_{i',t}}{\sum_{i'\neq i} LC_{i,i',t-1}} \end{aligned}$$

where $\vec{C}_{i,t} = [c_{i,k,t}]_{1\times K}$ is a normalized vector of knowledge score for each industry i, $r_{i',t}$ is the market capitalization-weighted (or equal-weighted) average return of firms in industry i' in month t in Panel A (Panel B). We sort industries into quintile portfolios at the end of each month based on the value of their $LCIRet_{i,t}$ during that month, and compute the average return of each quintile portfolio over the next month. The sample period is from January 1991 to April 2017.

	Panel A. Value-Weighted Returns						Panel B. Equal-Weighted Returns					
	Low	2	3	4	High	High-Low	Low	2	3	4	High	High-Low
Mean	6.58	8.68	9.32	10.73	11.76	5.19	6.82	9.83	11.93	12.82	16.06	9.23
Std	17.70	17.21	16.16	16.12	16.97	8.77	20.59	19.41	17.90	18.83	19.26	8.97
Skew	-0.52	-0.49	-0.60	-0.63	-0.54	-0.16	-0.16	0.03	-0.32	-0.23	-0.05	-0.28
Kurt	5.26	5.37	5.91	5.73	5.90	3.91	6.03	6.85	5.31	6.58	6.71	5.52
Sharpe	0.37	0.50	0.58	0.67	0.69	0.59	0.33	0.51	0.67	0.68	0.83	1.03

Table 3: Labor Connected Industry Returns and Other Firm Characteristics

This table presents average firm characteristics for industry portfolios sorted on the returns of their labor market connected industries ($LCIRet_{i,t}$). We measure $LCIRet_{i,t}$ for each industry i in month t by taking average of the returns of all other industries (i'), weighted by the strength of their connection to the subject industry through the labor market connectivity between between the two industries ($LC_{i,i',t}$). We denote $LC_{i,i',t}$ and $LCIRet_{i,t}$ as

$$
\begin{aligned}
LC_{i,i',t} &= -\frac{1}{2}\log\left(\sum_{k=1}^{K}(c_{i,k,t}-c_{i',k,t})^2\right) \\
LCIRet_{i,t} &= \frac{\sum_{i'\neq i} LC_{i,i',t-1}\times r_{i',t}}{\sum_{i'\neq i} LC_{i,i',t-1}}
\end{aligned}
$$

where $\vec{C}_{i,t} = [c_{i,k,t}]_{1\times K}$ is a normalized vector of knowledge score for each industry i, $r_{i',t}$ is the market capitalization-weighted average return of firms in industry i' in month t. Industries are ranked into quintile portfolios at the end of each month based on the value of their $LCIRet_{i,t}$ during that month. Each month, we then calculate for each quintile the average of various firm characteristics as of the most recent June relative to that month across firms within that quintile. Detailed definition of firm characteristics is provided in the Appendix. Newey-West adjusted t-statistics are given in parentheses and the sample period is from 1990 to 2016.

Quintile	BM	Size	$\text{Ret}_{i,t-12:t-2}$	Op. Lev.	Profitability	Innovation	Investment	Hiring
Low	0.661	2.628	0.167	1.086	0.332	0.159	0.309	0.048
2	0.702	2.522	0.162	1.161	0.355	0.151	0.304	0.041
3	0.693	2.682	0.154	1.133	0.359	0.149	0.297	0.040
4	0.688	2.582	0.154	1.168	0.356	0.156	0.309	0.042
High	0.657	2.613	0.175	1.081	0.328	0.159	0.315	0.047
Hi-Lo	-0.004	-0.149	0.008	-0.005	-0.003	0.000	0.007	-0.001
t-ratio	(-0.19)	(-0.22)	(1.49)	(-0.59)	(-1.24)	(-0.22)	(2.67)	(-0.62)

Table 4: Abnormal Returns on Industry Portfolios Sorted by Labor Market Connectedness

This table presents the summary statistics of the abnormal returns (alphas) and factor exposures (betas) of industry portfolios sorted by the lagged returns of labor market connected industries ($LCIRet_{i,t}$). To calculate abnormal returns, we consider the capital asset pricing model (CAPM), the three-factor model (FF3) of Fama and French (1993), the four-factor model (FFC4) of Carhart (1997), the five-factor model (FF5) of Fama and French (2015), the q-factor model (HXZ4) of Hou et al. (2015), the mispricing factor model (SY4) of Stambaugh and Yuan (2017), the behavioral factor model (DHS3) of Daniel et al. (2020), and the seven-factor model (FFCPS7) of Fama and French (2015), Carhart (1997), and Pastor and Stambaugh (2003). We measure $LCIRet_{i,t}$ for each industry-month by taking the average returns of all other industries, weighted by the strength of their connection to the subject industry through the labor market connectivity between industries i and i' ($LC_{i,i',t}$).

$$LCIRet_{i,t} = \frac{\sum_{i' \neq i} LC_{i,i',t-1} \times r_{i',t}}{\sum_{i' \neq i} LC_{i,i',t-1}} \quad \text{and} \quad LC_{i,i',t} \;=\; -\frac{1}{2} \log \left(\sum_{k=1}^{K} (c_{i,k,t} - c_{i',k,t})^2 \right)$$

where $\vec{C}_{i,t} = [c_{i,k,t}]_{1 \times K}$ is a normalized vector of knowledge score for each industry i, $r_{i',t}$ is the value-(equal-)weighted average returns of firms in industry i' in month t in Panel A (Panel B). We sort industries into quintile portfolios at the end of each month based on the value of their $LCIRet_{i,t}$, and compute the average return of each quintile portfolio over the next month. Newey-West adjusted t-statistics are given in parentheses and the sample period is from January 1991 to April 2017.

	Panel A. Value-Weighted Returns						Panel B. Equal-Weighted Returns					
	Low	2	3	4	High	High-Low	Low	2	3	4	High	High-Low
CAPM	-2.25	-0.06	1.05	2.47	3.23	5.48	-2.58	1.01	3.67	4.29	7.29	9.86
	(-1.05)	(-0.04)	(0.67)	(1.56)	(1.83)	(3.23)	(-0.99)	(0.37)	(1.48)	(1.65)	(2.91)	(5.85)
FF3	-3.87	-1.62	-0.58	1.03	1.66	5.53	-4.62	-1.07	1.48	2.16	4.95	9.57
	(-2.43)	(-1.14)	(-0.55)	(0.95)	(1.11)	(3.17)	(-2.38)	(-0.57)	(0.97)	(1.39)	(3.07)	(5.61)
FFC4	-2.86	-0.46	0.35	1.53	2.01	4.86	-2.00	1.31	3.65	4.38	6.80	8.81
	(-1.94)	(-0.36)	(0.38)	(1.40)	(1.21)	(2.33)	(-1.08)	(0.65)	(2.58)	(2.75)	(3.96)	(4.89)
FF5	-5.66	-3.39	-2.73	-0.89	-0.28	5.38	-3.96	-1.36	1.07	2.34	4.81	8.77
	(-3.44)	(-2.35)	(-2.65)	(-0.85)	(-0.20)	(2.73)	(-1.60)	(-0.59)	(0.59)	(1.29)	(2.94)	(4.21)
HXZ4	-4.85	-1.87	-1.16	-0.06	0.34	5.18	-1.49	1.03	3.70	4.82	7.23	8.72
	(-2.36)	(-1.07)	(-0.82)	(-0.05)	(0.20)	(2.17)	(-0.50)	(0.32)	(1.66)	(2.24)	(3.73)	(3.70)
SY4	-3.02	-0.80	-0.59	0.29	0.50	3.53	-0.18	2.50	4.96	5.56	7.12	7.31
	(-1.92)	(-0.57)	(-0.50)	(0.23)	(0.29)	(1.60)	(-0.08)	(1.15)	(2.69)	(2.83)	(3.48)	(3.62)
DHS3	-1.42	0.95	0.93	2.31	2.51	3.93	2.74	4.65	7.17	8.36	9.86	7.13
	(-0.80)	(0.60)	(0.73)	(1.71)	(1.43)	(1.82)	(0.91)	(1.45)	(2.62)	(2.85)	(3.37)	(3.60)
FFCPS7	-4.89	-2.66	-2.18	-0.69	-0.14	4.75	-2.23	0.14	2.47	3.64	5.96	8.20
	(-3.27)	(-2.17)	(-2.46)	(-0.68)	(-0.09)	(2.19)	(-1.06)	(0.07)	(1.64)	(2.23)	(3.67)	(4.09)

Panel C. FF5 Model Betas

	Low	2	3	4	High	High - Low
MKT	1.13	1.12	1.09	1.07	1.10	-0.03
	(23.20)	(32.51)	(39.18)	(42.49)	(42.36)	(-0.57)
SMB	0.44	0.43	0.40	0.40	0.44	0.00
	(5.64)	(6.77)	(7.03)	(7.95)	(9.89)	(0.07)
HML	0.23	0.21	0.22	0.14	0.17	-0.06
	(3.05)	(3.01)	(4.42)	(2.73)	(3.03)	(-0.92)
RMW	0.34	0.32	0.38	0.30	0.31	-0.03
	(3.37)	(4.19)	(5.00)	(6.98)	(7.22)	(-0.27)
CMA	-0.06	-0.03	-0.02	0.08	0.05	0.12
	(-0.59)	(-0.46)	(-0.29)	(1.54)	(0.79)	(0.89)

Panel D. HXZ4 Model Betas

	Low	2	3	4	High	High - Low
MKT	1.11	1.08	1.04	1.04	1.07	-0.04
	(18.38)	(22.12)	(24.31)	(32.14)	(30.49)	(-0.67)
SMB	0.30	0.28	0.23	0.29	0.33	0.03
	(1.35)	(1.52)	(1.00)	(2.57)	(3.54)	(0.41)
I/A	0.26	0.29	0.33	0.31	0.32	0.06
	(2.64)	(2.94)	(3.37)	(4.68)	(3.86)	(0.54)
ROE	0.14	0.03	0.07	0.11	0.11	-0.04
	(1.62)	(0.38)	(0.99)	(2.01)	(1.45)	(-0.32)

Panel E. SY4 Model Betas

	Low	2	3	4	High	High - Low
MKT	1.02	1.02	1.00	1.01	1.04	0.02
	(22.99)	(33.24)	(33.56)	(35.98)	(27.41)	(0.40)
SMB	0.36	0.34	0.31	0.34	0.40	0.04
	(1.65)	(1.96)	(1.59)	(2.79)	(4.02)	(0.45)
MGMT	0.09	0.08	0.18	0.15	0.16	0.07
	(1.25)	(1.03)	(2.75)	(2.06)	(1.82)	(1.21)
PERF	-0.09	-0.08	-0.08	-0.01	-0.01	0.08
	(-2.49)	(-1.77)	(-1.91)	(-0.19)	(-0.18)	(1.85)

Panel F. DHS3 Model Betas

	Low	2	3	4	High	High - Low
MKT	1.10	1.09	1.06	1.04	1.09	-0.01
	(21.54)	(28.05)	(25.91)	(30.23)	(28.28)	(-0.21)
PEAD	-0.26	-0.28	-0.20	-0.12	-0.05	0.20
	(-2.51)	(-3.20)	(-2.78)	(-1.78)	(-0.60)	(1.81)
FIN	0.07	0.07	0.12	0.08	0.09	0.02
	(1.21)	(1.35)	(2.85)	(1.58)	(1.62)	(0.36)

Table 5: GMM Test based on Macroeconomic Shocks

This table presents the abnormal returns (pricing errors) and the J-Statistics for the generalized method of moment (GMM) test. The empirical stochastic discount factor is of the form

$$M_t = 1 - b_M \times MKT_t - b_F \times F_t$$

where MKT_t is the market factor and F_t is a proxy for the second aggregate shock using the first difference (Δ) in one of the following aggregate variables in year t: a proxy for aggregate labor adjustment costs – the cross-sectional standard deviation of firm level hiring rate ($STDHN$), investment specific shocks ($iSHOCK$), aggregate labor market tightness (LMT), one component of capital reallocation shock – sales of property, plant and equipment ($SPPE$), another component of capital reallocation shock – mergers and acquisitions (AQC), and the aggregate capital reallocation shock – the sum of sales of property, plant and equipment and mergers and acquisitions ($SPPEAQC$). The test assets include five value-weighted portfolios sorted by $LCIRet_{i,t}$ as well as the arbitrage portfolio that takes a long position in industries in the highest $LCIRet_{i,t}$ quintile and a short position in industries in the lowest $LCIRet_{i,t}$ quintile. J-Statistic is the test statistic for over-identifying restrictions. The sample period is from 1991 to 2016.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta STDHN$	$iSHOCK$	ΔLMT	$\Delta SPPE$	ΔAQC	$\Delta SPPEAQC$
Low-LCIRet	-0.018	0.044	-0.015	-0.019	-0.010	-0.011
	(-0.685)	(0.871)	(-0.449)	(-0.662)	(-0.315)	(-0.399)
2	0.002	0.082	-0.002	-0.001	0.006	0.004
	(0.165)	(2.411)	(-0.127)	(-0.102)	(0.578)	(0.450)
3	0.016	0.060	0.016	0.012	0.019	0.018
	(1.081)	(2.237)	(0.950)	(0.997)	(1.316)	(1.336)
4	0.031	0.087	0.028	0.024	0.031	0.030
	(1.958)	(3.625)	(1.621)	(2.031)	(2.242)	(2.332)
High-LCIRet	0.046	0.129	0.033	0.031	0.039	0.038
	(3.017)	(5.874)	(2.198)	(3.101)	(3.231)	(3.242)
High-Low	0.065	0.085	0.048	0.050	0.048	0.049
	(4.127)	(1.715)	(2.051)	(1.993)	(1.963)	(2.101)
J-Statistic	33.139	22.140	21.437	14.467	17.807	18.414
p-value	(0.000)	(0.000)	(0.001)	(0.013)	(0.003)	(0.002)

Table 6: Industry-Level Fama-MacBeth Regressions

This table presents results from the industry-level Fama-MacBeth regressions of the form:

$$Ret_{i,t} = \beta_t^0 + \beta_t^1 \cdot LCIRet_{i,t-1} + \sum_{k=1}^{K} \beta_t^j \cdot X_{i,t-1}^k + \eta_{i,t}, \quad i = 1, \cdots, N_t$$

where $Ret_{i,t}$ is the return of industry i in month t, and $LCIRet_{i,t-1}$ and $X_{i,t-1}^k$ are the return to industry i's LCI portfolio and the k-th control variable at the end of month $t-1$. As control variables, we include the lagged return of industry i ($\text{Ret}_{i,t-1}$), its return between $t-12$ and $t-2$ ($\text{Ret}_{i,t-12:t-2}$), the lagged return of the portfolio industries that belong to the broader industry group of industry i ($\text{RetSIC2}_{i,t-1}$ and $\text{RetSIC2}_{i,t-12:t-2}$), defined by 2-digit SIC codes for years prior to 1997 and 3-digit NAICS code from 1997 onward, and the lagged return of a portfolio composed of its supplier and customer industries ($\text{IORet}_{i,t-1}$). We also include the (intra-industry) value-weighted average of the number of analysts (NumAnal), the percentage of institutional ownership (InstOwn), the log of market capitalization (Size), the book-to-market ratio (BM), the change in total assets (Inv), and the gross profitability (Prof). Newey-West adjusted t-statistics are given in parentheses and the sample period is from January 1991 to April 2017.

	Dependent Variable: $\text{Ret}_{i,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{LCIRet}_{i,t-1}$	0.366	0.372	0.300	0.297	0.288	0.271	0.433	0.416
	(3.402)	(3.528)	(2.915)	(3.086)	(2.777)	(2.569)	(3.171)	(3.101)
$\text{Ret}_{i,t-1}$		0.004	-0.007	-0.010	-0.007	-0.007	-0.004	-0.003
		(0.443)	(-0.683)	(-1.008)	(-0.678)	(-0.691)	(-0.400)	(-0.291)
$\text{RetSIC2}_{i,t-1}$			0.033	0.031	0.015	0.017	0.016	0.017
			(3.235)	(3.067)	(1.105)	(1.214)	(1.114)	(1.160)
$\text{Ret}_{i,t-12:t-2}$				0.008	0.008	0.008	0.009	0.008
				(2.058)	(1.979)	(2.124)	(2.165)	(2.163)
$\text{IORet}_{i,t-1}$					0.085	0.074	0.079	0.086
					(2.359)	(2.081)	(2.135)	(2.347)
$\text{RetSIC2}_{i,t-12:t-2}$						-0.002	-0.002	-0.002
						(-0.570)	(-0.620)	(-0.601)
$\text{LCIRet}_{i,t-12:t-2}$							0.007	-0.002
							(0.198)	(-0.049)
NumAnal								0.000
								(0.681)
InstOwn								0.001
								(0.302)
Size	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.194)	(1.098)	(0.987)	(0.769)	(0.628)	(0.645)	(0.562)	(-0.241)
BM	0.004	0.004	0.004	0.005	0.005	0.005	0.005	0.006
	(1.711)	(1.693)	(1.679)	(2.046)	(2.229)	(2.187)	(2.262)	(2.306)
Inv	-0.005	-0.005	-0.005	-0.004	-0.005	-0.005	-0.004	-0.004
	(-2.171)	(-1.965)	(-1.941)	(-1.722)	(-2.067)	(-1.929)	(-1.868)	(-1.796)
Prof	0.003	0.002	0.002	0.003	0.005	0.005	0.005	0.005
	(1.261)	(0.832)	(0.782)	(1.215)	(1.911)	(1.955)	(2.126)	(2.042)

Table 7: The Role of Informed Trading and Limits to Arbitrage

This table presents results from the industry-level Fama-MacBeth regressions of the form:

$$Ret_{i,t} = \beta_t^0 + \beta_t^1 \cdot LCIRet_{i,t-1} + \sum_{k=1}^{K} \beta_t^j \cdot X_{i,t-1}^k + \eta_{i,t}, \quad i = 1, \cdots, N_t$$

where $Ret_{i,t}$ is the return of industry i in month t, and $LCIRet_{i,t-1}$ and $X_{i,t-1}^k$ are the return to industry i's LCI portfolio and the k-th control variable at the end of month $t-1$. At the end of each month, we construct two portfolios: industries with above median level of the (intra-industry) value-weighted average number of analysts (Panel A), percentage of institutional holdings (Panel B), and idiosyncratic volatility (Panel C), and the other industries with below median level. The level of analyst coverage is constructed based on the analyst EPS forecast from the I/B/E/S detail detail history file. The level of institutional ownership is measured by the percentage of the shares outstanding for the firm that is held by institutional investors as reported in Thomson Financial's 13F Holdings database. The idiosyncratic volatility is computed as the standard deviation of the residuals from a regression of daily stock returns in the previous month on the Fama and French (1993) 3-factors. As control variables, we include the lagged return of industry i ($\text{Ret}_{i,t-1}$), its return between $t-12$ and $t-2$ ($\text{Ret}_{i,t-12:t-2}$), the lagged return of the portfolio industries that belong to the broader industry group of industry i ($\text{RetSIC2}_{i,t-1}$), defined by 2-digit SIC codes for years prior to 1997 and 3-digit NAICS code from 1997 onward, and the lagged return of a portfolio composed of its supplier and customer industries ($\text{IORet}_{i,t-1}$). We also include the log of market capitalization, the book-to-market ratio, the change in total assets, and the gross profitability. Newey-West adjusted t-statistics are given in parentheses and the sample period is from January 1991 to April 2017.

Dependent Variable: $\text{Ret}_{i,t}$									
	A. Analyst Coverage			B. Institutional Holdings			C. Idiosyncratic Volatility		
	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$\text{LCIRet}_{i,t-1}$	0.057	0.658	-0.601	0.252	0.625	-0.373	0.548	0.101	0.447
	(0.402)	(3.749)	(-2.846)	(1.848)	(3.916)	(-1.969)	(3.511)	(0.661)	(2.282)
$\text{Ret}_{i,t-1}$	-0.005	-0.004	-0.001	-0.001	-0.006	0.005	-0.015	-0.009	-0.006
	(-0.392)	(-0.338)	(-0.089)	(-0.084)	(-0.499)	(0.346)	(-1.162)	(-0.776)	(-0.361)
$\text{RetSIC2}_{i,t-1}$	-0.006	0.015	-0.021	0.004	0.011	-0.007	0.029	0.002	0.027
	(-0.339)	(0.820)	(-0.830)	(0.247)	(0.636)	(-0.296)	(1.661)	(0.149)	(1.185)
$\text{Ret}_{i,t-12:t-2}$	0.010	0.008	0.002	0.008	0.007	0.000	0.011	0.005	0.005
	(2.135)	(1.892)	(0.490)	(1.774)	(1.707)	(0.062)	(2.751)	(1.271)	(1.248)
$\text{IORet}_{i,t-1}$	0.058	0.088	-0.029	0.039	0.109	-0.070	0.054	0.060	-0.006
	(1.245)	(1.727)	(-0.438)	(0.865)	(2.204)	(-1.185)	(0.970)	(1.399)	(-0.093)

Table 8: Spillover in Wage, Labor Expenditure, and Employment

This table reports the relationship between labor expenditure across industries that are linked through the labor market. We run the following panel regression:

$$\Delta V_{i,y} = \beta_0 + \beta_1 \cdot \text{LCIRet}_{i,y-1} + \beta_2 \cdot \Delta V_{i,y-1} + \beta_3 \cdot Controls_{i,y-1} + \lambda_y + \epsilon_{i,y} \qquad \text{for (1) and (2)}$$

$$\Delta V_{i,y} = \beta_0 + \beta_1 \cdot \text{LCI-}V_{i,y-1} + \beta_2 \cdot \Delta V_{i,y-1} + \beta_3 \cdot Controls_{i,y-1} + \lambda_y + \epsilon_{i,y} \qquad \text{for (3) and (4)}$$

where $V_{i,y}$ is one of the labor-related variables that captures cross-effect of labor productivity shocks across industries: $Wage_{i,y}$ is the employment-weighted average of the hourly wages across all occupations in industry i in year y, $LaborExp_{i,y}$ is the total labor costs for industry i in year y, defined as the product of the employment and the associated wage in each occupation in industry i, aggregated across occupations in that industry, and $Empl_{i,y}$ is the total employment in industry i in year y. We measure $\text{LCIRet}_{i,y-1}$ ($\text{LCI-}V_{i,y-1}$) for each industry-year by taking average of portfolio returns (labor-related variables) of all other industries, weighted by the strength of their connection to the subject industry through the labor market connectivity between industries i and i' ($LC_{i,i',y}$): $\text{LCIRet}_{i,y} = \frac{\sum_{i' \neq i} LC_{i,i',y-1} \times ret_{i',y}}{\sum_{i' \neq i} LC_{i,i',y-1}}$ and $\text{LCI-}V_{i,y} = \frac{\sum_{i' \neq i} LC_{i,i',y-1} \times \Delta V_{i',y}}{\sum_{i' \neq i} LC_{i,i',y-1}}$. We include the return of industry i in year $y-1$ ($\text{Ret}_{i,y-1}$), the return of the industry portfolios that belong to the broader industry group of industry i in year $y-1$ ($\text{RetSIC2}_{i,y-1}$), and the return of its supplier and customer connected industries in year $y-1$ ($\text{IORet}_{i,y-1}$). λ_y is the year fixed effect and standard errors are clustered by year and industry. The sample period is from 1999 to 2016.

	A. $\Delta V_{i,y} = \Delta Wage_{i,y}$				B. $\Delta V_{i,y} = \Delta LaborExp_{i,y}$				C. $\Delta V_{i,y} = \Delta Empl_{i,y}$			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$\text{LCIRet}_{i,y-1}$	0.106	0.122			0.550	0.502			0.611	0.536		
	(2.890)	(3.213)			(7.289)	(6.427)			(8.669)	(7.307)		
$\text{LCI-}V_{i,y-1}$			0.840	0.848			0.394	0.402			0.164	0.182
			(4.222)	(4.250)			(6.652)	(6.805)			(3.505)	(3.892)
$\Delta V_{i,y-1}$	-0.241	-0.241	-0.256	-0.256	0.001	0.001	-0.026	-0.029	0.026	0.027	0.019	0.018
	(-13.385)	(-13.373)	(-13.953)	(-13.951)	(0.061)	(0.053)	(-1.301)	(-1.450)	(1.718)	(1.806)	(1.231)	(1.154)
$\text{Ret}_{i,y-1}$	0.011	0.015	0.013	0.014	0.031	0.021	0.040	0.020	0.024	0.014	0.042	0.021
	(3.231)	(3.211)	(3.817)	(3.106)	(4.355)	(2.248)	(5.638)	(2.171)	(3.751)	(1.769)	(6.705)	(2.505)
$\text{RetSIC2}_{i,y-1}$		-0.006		-0.001		0.019		0.033		0.015		0.037
		(-0.986)		(-0.179)		(1.537)		(2.780)		(1.399)		(3.449)
$\text{IORet}_{i,y-1}$		-0.022		-0.017		0.059		0.110		0.126		0.123
		(-1.140)		(-0.897)		(1.492)		(2.819)		(3.793)		(3.556)

Table 9: Labor Productivity Spillover

This table reports the relationship between labor productivity across industries that are linked through the labor market. We run the following panel regression:

$$\begin{aligned} \Delta LP_{i,y} &= \beta_0 + \beta_1 \cdot \text{LCIRet}_{i,y-1} + \beta_2 \cdot \Delta LP_{i,y-1} + \beta_3 \cdot Controls_{i,y-1} + \lambda_y + \epsilon_{i,y} && \text{for (1) and (2)} \\ \Delta LP_{i,y} &= \beta_0 + \beta_1 \cdot \text{LCI-LP}_{i,y-1} + \beta_2 \cdot \Delta LP_{i,y-1} + \beta_3 \cdot Controls_{i,y-1} + \lambda_y + \epsilon_{i,y} && \text{for (3) and (4)} \end{aligned}$$

where $\Delta LP_{i,y}$ is a measure of labor productivity growth of industry i in year y. We use the annual growth rate of sales per employee in Panel A and that of output per hour of labor sourced from Bureau of Labor Statistics in Panel B. We measure $\text{LCIRet}_{i,y-1}$ ($\text{LCI-LP}_{i,y-1}$) for each industry-year by taking average of portfolio returns (labor productivity growth rates) of all other industries, weighted by the strength of their connection to the subject industry through the labor market connectivity between industries i and i' ($LC_{i,i',y}$): $\text{LCIRet}_{i,y} = \frac{\sum_{i' \neq i} LC_{i,i',y-1} \times ret_{i',y}}{\sum_{i' \neq i} LC_{i,i',y-1}}$ and $\text{LCI-LP}_{i,y} = \frac{\sum_{i' \neq i} LC_{i,i',y-1} \times \Delta LP_{i',y}}{\sum_{i' \neq i} LC_{i,i',y-1}}$. We include the return of industry i in year $y-1$ ($\text{Ret}_{i,y-1}$), the return of the industry portfolios that belong to the broader industry group of industry i in year $y-1$ ($\text{RetSIC2}_{i,y-1}$), and the return of its supplier and customer connected industries in year $y-1$ ($\text{IORet}_{i,y-1}$). λ_y is the year fixed effect and standard errors are clustered by year and industry. The sample period is from 1991 to 2016.

	A. Dependent Variable: $\Delta LP_{i,y}$ ΔSales per Employment				B. Dependent Variable: $\Delta LP_{i,y}$ ΔOutput per hour of labor			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$\text{LCIRet}_{i,y-1}$	0.217	0.214			0.146	0.156		
	(2.589)	(2.458)			(1.990)	(2.042)		
$\text{LCI-LP}_{i,y-1}$			0.663	0.632			0.539	0.523
			(4.567)	(4.319)			(2.182)	(2.112)
$\Delta LP_{i,y-1}$	-0.026	-0.026	-0.028	-0.028	0.280	0.282	0.277	0.279
	(-1.723)	(-1.737)	(-1.811)	(-1.814)	(15.340)	(15.417)	(15.145)	(15.217)
$\text{Ret}_{i,y-1}$	0.036	0.044	0.038	0.042	0.017	0.022	0.018	0.022
	(4.768)	(4.502)	(5.029)	(4.331)	(3.030)	(3.371)	(3.231)	(3.286)
$\text{RetSIC2}_{i,y-1}$		-0.020		-0.013		-0.017		-0.014
		(-1.508)		(-1.011)		(-1.803)		(-1.447)
$\text{IORet}_{i,y-1}$		0.085		0.080		0.049		0.055
		(2.059)		(1.950)		(1.620)		(1.818)

Table 10: Spillover in Profitability

This table reports the relationship between profitability across industries that are linked through the labor market. We run the following panel regression:

$$\Delta Prof_{i,y} = \beta_0 + \beta_1 \cdot \text{LCIRet}_{i,y-1} + \beta_2 \cdot \Delta Prof_{i,y-1} + \beta_3 \cdot Controls_{i,y-1} + \lambda_y + \epsilon_{i,y} \text{ for (1) and (2)}$$
$$\Delta Prof_{i,y} = \beta_0 + \beta_1 \cdot \text{LCI-Prof}_{i,y-1} + \beta_2 \cdot \Delta Prof_{i,y-1} + \beta_3 \cdot Controls_{i,y-1} + \lambda_y + \epsilon_{i,y} \text{ for (3) and (4)}$$

where $\Delta prof_{i,y}$ is percentage change in the profitability for industry i over year y. The industry-level profitability is calculated as the sum of the total revenue (REVT) minus cost of goods sold (COGS) divided by the sum of total assets (AT) following Novy-Marx (2013). We measure $\text{LCIRet}_{i,y-1}$ (LCI-$Prof_{i,y-1}$) for each industry-year by taking average of portfolio returns (profitability growth rates) of all other industries, weighted by the strength of their connection to the subject industry through the labor market connectivity between industries i and i' ($LC_{i,i',y}$): $\text{LCIRet}_{i,y} = \frac{\sum_{i' \neq i} LC_{i,i',y-1} \times ret_{i',y}}{\sum_{i' \neq i} LC_{i,i',y-1}}$ and LCI-$Prof_{i,y} = \frac{\sum_{i' \neq i} LC_{i,i',y-1} \times \Delta Prof_{i',y}}{\sum_{i' \neq i} LC_{i,i',y-1}}$. We include the return of industry i in year $y-1$ ($\text{Ret}_{i,y-1}$), the return of the industry portfolios that belong to the broader industry group of industry i in year $y-1$ ($\text{RetSIC2}_{i,y-1}$), and the return of its supplier and customer connected industries in year $y-1$ ($\text{IORet}_{i,y-1}$). λ_y is the year fixed effect and standard errors are clustered by year and industry. The sample period is from 1991 to 2016.

	Dependent Variable: $\Delta Prof_{i,y}$			
	(1)	(2)	(3)	(4)
$\text{LCIRet}_{i,y-1}$	0.630	0.518		
	(2.791)	(2.196)		
$\text{LCI-Prof}_{i,y-1}$			0.067	0.065
			(2.108)	(2.055)
$\Delta Prof_{i,y-1}$	-0.034	-0.034	-0.067	-0.066
	(-1.329)	(-1.330)	(-3.924)	(-3.891)
$\text{Ret}_{i,y-1}$	0.114	0.130	0.089	0.108
	(5.725)	(4.834)	(6.197)	(6.147)
$\text{RetSIC2}_{i,y-1}$		-0.047		-0.058
		(-1.346)		(-2.395)
$\text{IORet}_{i,y-1}$		0.370		0.230
		(3.417)		(2.969)

Table 11: Labor Productivity Spillover and Return Predictability

This table presents results from the industry-level monthly Fama-MacBeth regressions of the form:

$$Ret_{i,t} = \beta_t^0 + \beta_t^1 \cdot \text{LCI-LP}_{i,lagged} + \sum_{k=1}^{K} \beta_t^j \cdot X_{i,t-1}^k + \eta_{i,t}, \quad i = 1, \cdots, N_t$$

where $Ret_{i,t}$ is the return of industry i in month t, and $X_{i,t-1}^k$ is the k-th control variable at the end of month $t-1$. We use the annual growth rate of sales per employee in Panel A and that of output per hour of labor sourced from Bureau of Labor Statistics in Panel B as a measure of labor productivity growth of industry i in year y ($\Delta LP_{i,y}$). We measure LCI-LP for each industry-year by taking average of labor productivity growth rates of all other industries, weighted by the strength of their connection to the subject industry through the labor market connectivity between industries i and i' ($LC_{i,i',y}$): $\text{LCI-LP}_{i,y} = \frac{\sum_{i' \neq i} LC_{i,i',y-1} \times \Delta LP_{i',y}}{\sum_{i' \neq i} LC_{i,i',y-1}}$. For $\text{LCI-LP}_{i,lagged}$, we lag $\text{LCI-LP}_{i,y}$ by a minimum of 4-months to ensure the availability of financial and macro-economic data to investors. See Table 6 for the definitions of other control variables. Newey-West adjusted t-statistics are given in parentheses and the sample period is from January 1991 to April 2017.

	A. LP =Sales per Employment				B. LP =Output per hour of labor			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Intercept	-0.008	-0.006	-0.004	-0.005	-0.004	-0.003	-0.004	-0.003
	(-0.923)	(-0.786)	(-0.525)	(-0.567)	(-0.407)	(-0.318)	(-0.405)	(-0.288)
$\text{LCI-LP}_{i,lagged}$	0.123	0.125	0.136	0.130	0.331	0.300	0.328	0.278
	(2.071)	(2.227)	(2.287)	(2.189)	(2.567)	(2.372)	(2.257)	(1.918)
$\text{Ret}_{i,t-1}$		-0.012	-0.011	-0.012		-0.018	-0.018	-0.016
		(-1.145)	(-0.991)	(-1.082)		(-1.559)	(-1.424)	(-1.250)
$\text{RetSIC2}_{i,t-1}$		0.039	0.020	0.019		0.046	0.042	0.039
		(3.456)	(1.447)	(1.379)		(3.333)	(2.165)	(2.059)
$\text{Ret}_{i,t-12:t-2}$			0.010	0.010			0.015	0.015
			(2.558)	(2.463)			(3.308)	(3.181)
$\text{IORet}_{i,t-1}$			0.138	0.140			0.120	0.128
			(3.347)	(3.387)			(2.343)	(2.490)
$\text{RetSIC2}_{i,t-12:t-2}$			-0.003	-0.003			-0.006	-0.007
			(-0.627)	(-0.714)			(-1.179)	(-1.220)
$\Delta\text{LP}_{i,lagged}$				0.006				0.001
				(1.440)				(0.151)
Size	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.452)	(1.346)	(0.591)	(0.578)	(0.443)	(0.451)	(0.016)	(0.016)
BM	0.004	0.004	0.005	0.005	0.000	0.001	0.005	0.005
	(1.634)	(1.696)	(1.820)	(1.932)	(0.044)	(0.209)	(1.426)	(1.416)
Inv	-0.006	-0.005	-0.007	-0.007	-0.004	-0.003	-0.004	-0.004
	(-2.051)	(-1.880)	(-2.381)	(-2.566)	(-1.258)	(-0.979)	(-1.069)	(-1.169)
Prof	0.004	0.002	0.005	0.005	0.001	-0.002	0.003	0.003
	(1.195)	(0.611)	(1.693)	(1.876)	(0.149)	(-0.490)	(0.744)	(0.844)

Table 12: Labor Productivity Spillover and Adoption Capacity

This table presents the summary of the results from the Fama-MacBeth regressions of the form

$$Ret_{i,t} = \beta_t^0 + \beta_t^1 \cdot LCIRet_{i,t-1} + \sum_{k=1}^{K} \beta_t^j \cdot X_{i,t-1}^k + \eta_{i,t}, \quad i = 1, \cdots, N_t$$

where $Ret_{i,t}$ is the return of industry i in month t, and $LCIRet_{i,t-1}$ and $X_{i,t-1}^k$ are the return to industry i's LCI portfolio and the k-th control variable at the end of month $t-1$. We split industries into two subsamples based on the average firm level innovation (Panel A), the average firm level profitability (Panel B), and the industry level labor mobility (Panel C), where the level of innovations are proxied by the citation-weighted value of the firm's patents following Kogan et al. (2017), the profitability is measured as the total revenue (REVT) minus cost of goods sold (COGS) divided by total assets (AT) following Novy-Marx (2013), and the degree of labor mobility is defined as the industry's average reliance on occupations that are most common across all industries following Donangelo (2014). We include the lagged return of industry i ($\text{Ret}_{i,t-1}$), its return between $t-12$ and $t-2$ ($\text{Ret}_{i,t-12:t-2}$), and the lagged return of the portfolio industries that belong to the broader industry group of industry i ($\text{RetSIC2}_{i,t-1}$) and the lagged return of a portfolio composed of its supplier and customer industries ($\text{IORet}_{i,t-1}$). Newey-West adjusted t-statistics are given in parentheses and the sample period is from January 1991 to April 2017.

Dependent Variable: $\text{Ret}_{i,t}$									
	A. Innovation			B. Profitability			C. Labor Mobility		
	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$\text{LCIRet}_{i,t-1}$	0.720	0.315	0.405	0.523	0.063	0.460	0.623	0.116	0.507
	(2.789)	(2.012)	(1.92)	(3.196)	(0.434)	(2.429)	(2.65)	(0.658)	(2.162)
$\text{Ret}_{i,t-1}$	0.009	-0.004	0.012	-0.016	0.013	-0.029	0.000	0.004	-0.004
	(0.646)	(-0.248)	(0.703)	(-1.249)	(0.959)	(-1.754)	(0.026)	(0.252)	(-0.197)
$\text{RetSIC2}_{i,t-1}$	0.017	0.027	-0.010	0.031	0.007	0.024	0.002	0.022	-0.020
	(0.985)	(1.331)	(-0.418)	(1.763)	(0.394)	(1.004)	(0.086)	(1.139)	(-0.743)
$\text{Ret}_{i,t-12:t-2}$	0.008	0.010	-0.003	0.009	0.010	-0.001	0.013	0.004	0.010
	(1.706)	(1.951)	(-0.579)	(2.025)	(2.358)	(-0.309)	(3.116)	(0.835)	(2.128)
$\text{IORet}_{i,t-1}$	0.086	0.029	0.057	0.026	0.106	-0.080	0.044	0.059	-0.015
	(1.769)	(0.433)	(0.815)	(0.518)	(2.057)	(-1.26)	(0.622)	(1.012)	(-0.184)

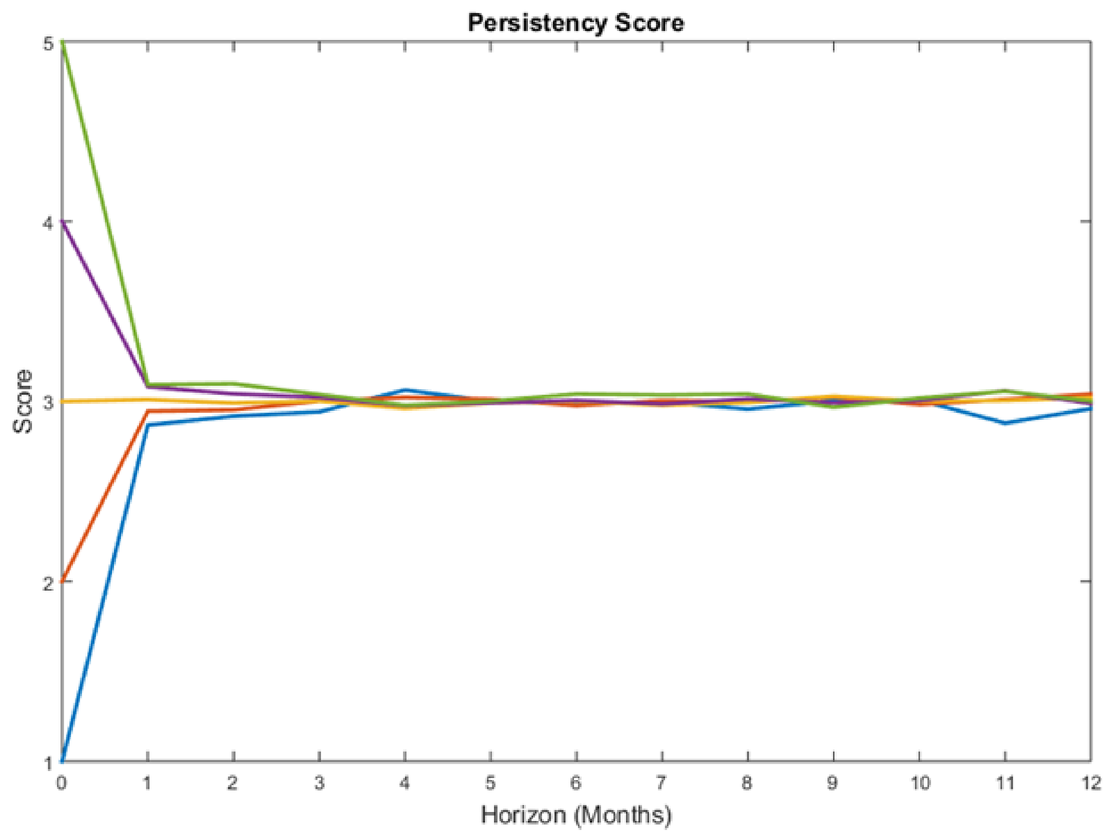

Figure 1: Persistency Scores

This figure plots the transition of industries across $LCIRet$ quintiles over various horizons. At the beginning of each month we give a score to each industry based on the quintile that it belongs to (5 for the highest quintile, 1 for the lowest quintile). We then keep track of these scores for the same industries over time and measure the average value of those scores for industries that initially belonged to each quintile. A persistent $LCIRet$ implies that industries should remain in the same quintile over a relatively long period of time. The sample period is from January 1991 to April 2017.

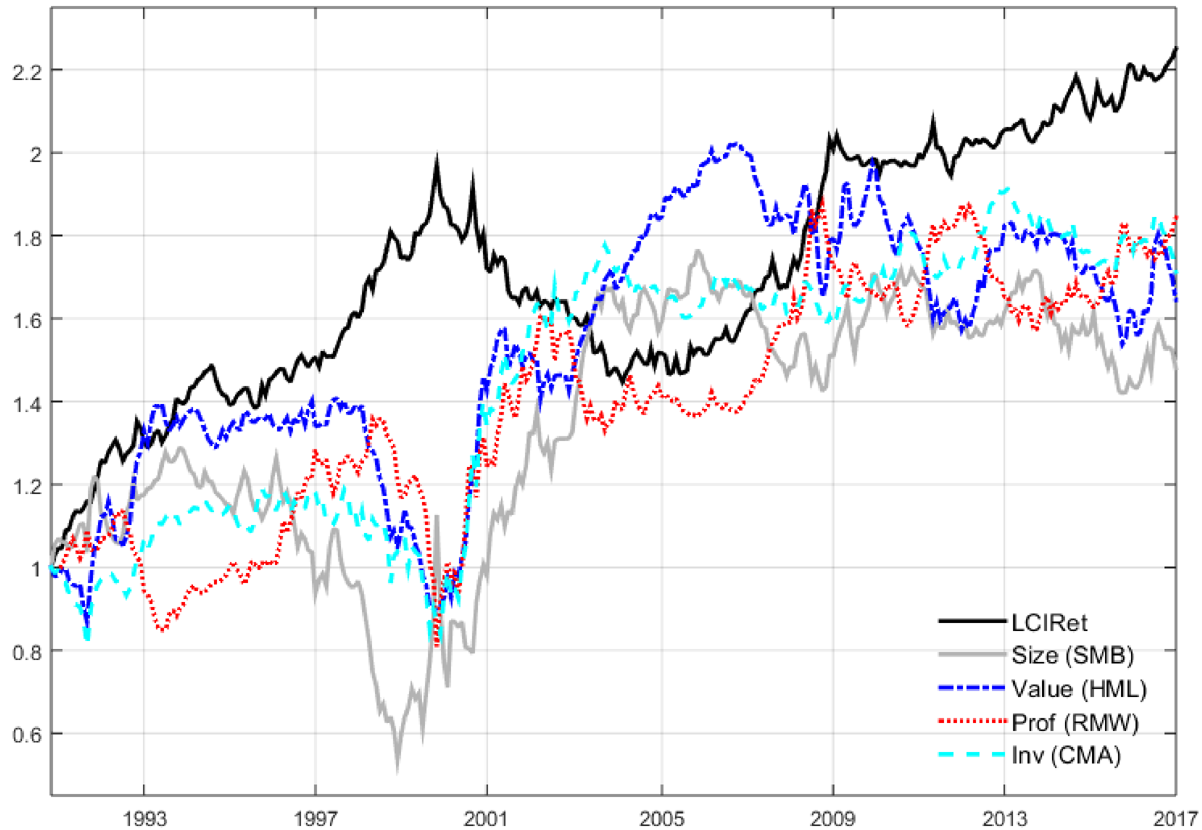

Figure 2: Cumulative Returns

This figure plots the time series of cumulative returns of the High-minus-Low LCIRet-sorted portfolios. To construct the LCIRet-sorted portfolios, we first measure $LCIRet_{i,t}$ for each industry-month by taking average returns of all other industries, weighted by the strength of their connection to the subject industry through the labor market connectivity between industries i and i' ($LC_{i,i',t}$). We then sort industries into quintile portfolios at the end of each month based on the value of their $LCIRet_{i,t}$ during that month, and compute the return of each quintile portfolio over the next month. For comparison, we also plot the time series of cumulative returns of the SMB (small minus big stocks), HML (high minus low book-to-market stocks), RMW (robust minus weak operating profitability stocks), and CMA (low minus high investment firms) factors. All factor returns are constructed using univariate sorts on those firm characteristics and the data are obtained from Kenneth French's webpage. The sample period is from January 1991 to April 2017.

Table A1: Summary Statistics of Double-sorted Portfolios

This table presents the summary statistics of the return of double-sorted industry portfolios. We form 25 portfolios at the end of each month by double-sorting stocks based on the lagged returns of labor market connected industries ($LCIRet_{i,t-1}$) and one of the following variables: the lagged return of the industry i ($\text{Ret}_{i,t-1}$) in Panel A, the return of industry i between $t-12$ and $t-2$ ($\text{Ret}_{i,t-12:t-2}$) in Panel B, the lagged returns of its supplier and customer connected industries ($\text{IORet}_{i,t-1}$) in Panel C, and the lagged return of the broader industry group of industry i ($\text{RetSIC2}_{i,t-1}$) in Panel D. Industry i's return is measured as the market capitalization-weighted (or equal-weighted) average return of firms in industry i' in month t in the left (right) columns. The sample period is from January 1991 to April 2017.

	MktCap Weighted						Equally Weighted					
	Low LCRet	2	3	4	High LCRet	High-Low LCRet	Low LCRet	2	3	4	High LCRet	High-Low LCRet
Panel A. Sorting on $\text{Ret}_{i,t-1}$												
Low	-1.54	5.45	4.99	5.93	6.37	7.91	-2.91	2.53	7.97	7.66	8.74	11.65
2	5.17	6.15	7.21	9.88	10.64	5.46	2.63	6.18	6.14	9.05	12.69	10.06
3	5.73	8.46	7.54	9.77	12.99	7.26	3.53	7.38	8.75	9.42	13.24	9.71
4	6.57	7.11	9.31	8.75	10.03	3.46	8.31	10.61	11.28	13.39	13.56	5.25
High	7.33	7.03	8.93	11.14	9.33	2.00	9.84	11.44	15.72	13.66	20.79	10.95
High-Low	8.87	1.59	3.94	5.21	2.96		12.75	8.91	7.75	6.00	12.05	
Panel B. Sorting on $\text{Ret}_{i,t-12:t-2}$												
Low	1.31	-0.60	2.20	4.02	4.13	2.82	-3.58	-0.01	-0.50	2.38	4.31	7.90
2	2.92	6.21	4.02	5.76	6.51	3.59	0.26	3.80	6.28	5.53	8.28	8.02
3	2.00	4.75	6.56	10.79	6.90	4.90	2.25	5.60	8.75	10.36	12.07	9.82
4	0.98	7.40	6.72	7.34	11.52	10.54	1.60	7.19	9.46	9.79	14.29	12.69
High	4.44	7.03	8.03	9.67	10.49	6.05	5.27	6.34	10.98	10.84	15.36	10.08
High-Low	3.14	7.63	5.83	5.65	6.36		8.86	6.35	11.48	8.46	11.05	
Panel C. Sorting on $\text{IORet}_{i,t-1}$												
Low	1.16	5.09	2.00	9.23	7.12	5.96	1.26	6.68	9.64	6.24	10.69	9.43
2	3.74	8.69	7.30	10.43	13.11	9.37	1.28	9.92	11.10	8.28	13.63	12.35
3	2.66	4.71	9.15	6.25	11.00	8.34	6.02	7.65	8.18	9.44	13.70	7.68
4	7.57	9.72	8.30	10.08	8.86	1.29	6.37	7.05	11.90	11.05	14.72	8.35
High	6.88	8.07	7.00	6.53	13.09	6.21	4.07	9.26	10.78	13.25	17.51	13.44
High-Low	5.72	2.98	5.00	-2.69	5.97		2.80	2.58	1.14	7.01	6.82	
Panel D. Sorting on $\text{RetSIC2}_{i,t-1}$												
Low	0.03	3.00	4.67	8.94	9.48	9.45	0.26	0.35	4.97	7.35	6.65	6.40
2	5.56	4.33	8.77	7.74	8.59	3.03	0.36	6.57	8.90	9.50	10.72	10.36
3	6.46	8.37	5.19	9.36	11.54	5.08	6.26	8.65	11.25	10.67	14.89	8.63
4	4.01	9.00	10.96	8.78	8.51	4.50	5.19	8.74	10.20	12.73	14.78	9.58
High	7.05	9.43	9.45	10.32	11.68	4.63	9.12	13.66	14.48	13.49	21.79	12.67
High-Low	7.02	6.43	4.78	1.39	2.19		8.86	13.31	9.51	6.15	15.14	

Table A2: Fama-MacBeth Regression (Firm-level)

This table presents results from the firm-level Fama-MacBeth regressions of the form:

$$Ret_{n,t} = \beta_t^0 + \beta_t^1 \cdot LCIRet_{n,i,t-1} + \sum_{k=1}^{K} \beta_t^j \cdot X_{n,t-1}^k + \eta_{i,t}, \quad n = 1, \cdots, N_t$$

where $Ret_{n,t}$ is the return of firm n in month t, and $LCIRet_{n,i,t-1}$ is the return to industry i's LCI portfolio based on the firm n's industry membership and $X_{n,t-1}^k$ is the k-th control variable at the end of month $t-1$. As control variables, we include the short-term reversal: the lagged return of firm n ($\text{Ret}_{n,t-1}$), the momentum: the return between $t-12$ and $t-2$ ($\text{Ret}_{n,t-12:t-2}$), the long-term reversal: the return between $t-60$ and $t-13$ ($\text{Ret}_{n,t-60:t-13}$), the CAPM beta based on rolling 1-year regression using daily returns (Beta), the lagged returns of industry i based on the firm n's industry membership ($\text{IndRet}_{n,i,t-1}$ and $\text{IndRet}_{n,i,t-12:t-2}$), the lagged return of a portfolio composed of its supplier and customer industries ($\text{IndIORet}_{n,i,t-1}$), the number of analysts (NumAnal), the percentage of institutional ownership (InstOwn), the log of market capitalization (Size), the book-to-market ratio, the change in total assets (Inv), and the gross profitability (Prof). Newey-West adjusted t-statistics are given in parentheses and the sample period is from January 1991 to April 2017.

	Dependent Variable: $\text{Ret}_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
LCIRet	0.629	0.670	0.649	0.564	0.493	0.486
	(4.722)	(5.246)	(5.463)	(5.503)	(4.546)	(4.485)
Rev		-0.024	-0.026	-0.029	-0.037	-0.037
		(-4.626)	(-5.264)	(-6.070)	(-8.336)	(-8.355)
Mom			-0.001	-0.002	-0.005	-0.004
			(-0.338)	(-1.004)	(-1.881)	(-1.810)
RevLT				-0.005	-0.005	-0.005
				(-5.940)	(-6.164)	(-6.186)
Beta				0.002	0.001	0.001
				(0.643)	(0.528)	(0.543)
IndRev					0.063	0.064
					(6.773)	(6.887)
IndMom					0.014	0.015
					(5.765)	(5.989)
IndIORet					0.079	0.083
					(2.186)	(2.303)
NumAnal						0.000
						(4.448)
InstOwn						-0.005
						(-2.774)
Size	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(-6.425)	(-6.112)	(-5.871)	(-3.807)	(-3.744)	(-3.923)
BM	0.003	0.003	0.002	0.000	0.001	0.001
	(1.893)	(2.015)	(1.805)	(0.307)	(1.139)	(1.142)
Inv	-0.009	-0.009	-0.009	-0.005	-0.004	-0.004
	(-6.988)	(-7.268)	(-7.583)	(-4.646)	(-4.781)	(-4.833)
Prof	0.007	0.006	0.006	0.007	0.008	0.008
	(3.365)	(3.295)	(3.210)	(3.508)	(4.523)	(4.580)

Table A3: Capital Productivity and Intermediate Purchases Productivity

This table reports the relationship between capital (intermediate purchase) productivity across industries that are linked through the labor market. We run the following panel regression:

$$\begin{aligned} \Delta CP_{i,y} &= \beta_0 + \beta_1 \cdot \text{LCIRet}_{i,y-1} + \Delta CP_{i,y-1} + Controls_{i,y-1} + \lambda_y + \epsilon_{i,y} && \text{for Panel A} \\ \Delta IPP_{i,y} &= \beta_0 + \beta_1 \cdot \text{LCIRet}_{i,y-1} + \Delta IPP_{i,y-1} + Controls_{i,y-1} + \lambda_y + \epsilon_{i,y} && \text{for Panel B} \end{aligned}$$

where $\Delta CP_{i,y}$ measures the rate at which capital is used to produce output of goods and services of industry i in year y and $\Delta IPP_{i,y}$ measures the rate at which intermediate purchases are consumed to produce output of goods and services of industry i in year y. We measure $\text{LCIRet}_{i,y-1}$ for each industry-year by taking average of portfolio returns (labor productivity growth rates) of all other industries, weighted by the strength of their connection to the subject industry through the labor market connectivity between industries i and i' ($LC_{i,i',y}$): $\text{LCIRet}_{i,y} = \frac{\sum_{i' \neq i} LC_{i,i',y-1} \times ret_{i',y}}{\sum_{i' \neq i} LC_{i,i',y-1}}$. We include the return of industry i in year $y-1$ ($\text{Ret}_{i,y-1}$), the return of the industry portfolios that belong to the broader industry group of industry i in year $y-1$ ($\text{RetSIC2}_{i,y-1}$), and the return of its supplier and customer connected industries in year $y-1$ ($\text{IORet}_{i,y-1}$). λ_y is the year fixed effect and standard errors are clustered by year and industry. The sample period is from 1991 to 2016.

	A. Dependent Variable: $\Delta CP_{i,y}$ ΔCapital Productivity		B. Dependent Variable: $\Delta IPP_{i,y}$ ΔIntermediate Purchases Productivity	
	(1)	(2)	(3)	(4)
$\text{LCIRet}_{i,y-1}$	0.178	0.199	-0.066	0.029
	(1.148)	(1.215)	(-0.432)	(0.177)
$\Delta CP_{i,y-1}$	0.252	0.253		
	(10.906)	(10.938)		
$\Delta IPP_{i,y-1}$			0.205	0.204
			(8.333)	(8.261)
$\text{Ret}_{i,y-1}$	0.039	0.042	0.014	0.020
	(5.214)	(4.861)	(2.134)	(2.568)
$\text{RetSIC2}_{i,y-1}$		-0.012		-0.012
		(-0.975)		(-1.050)
$\text{IORet}_{i,y-1}$		0.033		-0.038
		(0.840)		(-1.089)

Table A4: Labor Market Network (LMN) driven Momentum Factor

In Panel A (Panel B), at the end of each month, stocks (industries) are first sorted into two size groups; Small and Big, and then stocks (industries) in each size groups are further sorted into three $LCIRet$ groups; Low, Mid, and High. The labor market network driven momentum factor is the average of the two high-low value-weighted portfolio returns in each size groups. The first column in Panel A (Panel B) reports the average return on the labor market network driven *stock*-(*industry*-) momentum factor. The last four columns in Panel A (Panel B) present the abnormal returns (alphas) and factor exposures (betas) of the labor market network driven *stock*-(*industry*-) momentum factor. The alphas and factor exposures are estimated using the stock market factor of the capital asset pricing model (CAPM) and the stock, industry, and customer momentum factors of Carhart (1997), Moskowitz and Grinblatt (1999), and Menzly and Ozbas (2010), respectively. Newey-West adjusted t-statistics are given in parentheses and the sample period is from January 1991 to April 2017.

Panel A. Labor market network driven *stock*-momentum factor

	MOM_{LMN}^{stock}	MOM_{LMN}^{stock}	MOM_{LMN}^{stock}	MOM_{LMN}^{stock}	MOM_{LMN}^{stock}
$ALPHA$	7.04	7.65	6.76	6.88	5.24
	(3.17)	(3.80)	(3.40)	(3.41)	(3.54)
MKT		-0.07	-0.04	-0.06	-0.02
		(-1.25)	(-0.61)	(-0.93)	(-0.31)
MOM^{stock}			0.11		
			(1.00)		
MOM^{ind}				0.10	
				(0.97)	
MOM^{cus}					0.49
					(4.95)

Panel B. Labor market network driven *industry*-momentum factor

	MOM_{LMN}^{ind}	MOM_{LMN}^{ind}	MOM_{LMN}^{ind}	MOM_{LMN}^{ind}	MOM_{LMN}^{ind}
$ALPHA$	4.35	4.88	4.37	4.43	3.33
	(3.27)	(3.81)	(3.16)	(3.18)	(3.02)
MKT		-0.06	-0.05	-0.06	-0.03
		(-1.94)	(-1.32)	(-1.60)	(-1.35)
MOM^{stock}			0.06		
			(1.40)		
MOM^{ind}				0.06	
				(1.34)	
MOM^{cus}					0.30
					(8.37)