Sectoral Labor Reallocation and Return Predictability

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Abstract

Sectoral labor reallocation shocks change the optimal allocation of workers across industries. We show that the cross-sectional dispersion in industry-specific stock returns (CSV) serves as a good proxy for this type of labor market shocks. CSV predicts aggregate unemployment growth as well as the ex-post mismatch between job seekers and vacancies across sectors. We find that CSV has strong and robust predictive power for future stock market returns and easily outperforms 12 well-know existing predictive variables. In predictive regressions, the one-year out-of-sample R^2 is as high as 12.56%. We propose a production-based asset pricing model in which sectoral labor reallocation shocks generate return predictability through time–varying exposure to aggregate productivity risk. When the need for labor reallocation across industries arises, industries are more likely to hire workers from other industries. They therefore face higher adjustment costs, impeding them from fully responding to aggregate economic fluctuations and lowering their aggregate risk exposure. New testable implications are supported by the data.

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I Introduction

Many of the fundamental shocks that drive economic growth also lead to the reallocation of workers across industries.[1] For instance, technological development and changes to consumer preferences can affect the match between wants and resources across different sectors in the economy (Black, 1995). As a result, the optimal allocation of human capital across sectors changes. Sectoral labor reallocation shocks are structural (Blanchard and Diamond, 1989; Brainard and Cutler, 1993; Loungani and Trehan, 1997) and they are related to aggregate economic outcomes such as unemployment (e.g., Lilien, 1982; Loungani et al., 1990; Şahin et al., 2014; Kalay et al. 2018).Given that labor is a key input factor for most firms, a natural next question is whether and how sectoral labor reallocation shocks affect expected stock returns.[2]

We show, both empirically and theoretically, that these shocks to the labor market lead to very strong and robust time series predictability of future stock market returns. Our proxy for sectoral shifts outperforms a long list of alternative predictors of future stock market returns and it leads to economically sizeable gains when incorporated in a trading strategy. The mechanism relies on time-varying exposures to aggregate productivity risk. In the presence of sectoral shifts, high productivity industries face higher labor adjustment costs as they are more likely to need to hire from workers from other industries. This gives rise to regions of inactivity in these firms' optimal hiring policy, rendering their dividends less sensitive to aggregate productivity shocks. As firms in high-productivity industries constitute a relatively large market capitalizationthe exposure of the value-weighted equity market portfolio to aggregate risk declines also, leading to a lower market risk premium.

A well-known proxy for sectoral labor reallocation shocks is the cross-sectional dispersion in industry stock returns (e.g., Loungani et al., 1990; Brainard and Cutler, 1993; Loungani and Trehan, 1997). A higher dispersion in returns across industries implies a greater need for sectoral labor reallocation.[3] We use the cross-sectional return volatility (CSV) of past 12-month industry-

[1] As argued by, among others, Dixit and Rob (1994).

[2] Throughout the paper, we use sectoral labor reallocation shocks and sectoral shifts interchangeably.

[3] Lilien (1982) first showed the link between sectoral labor reallocation and aggregate unemployment. He focuses on the cross-industry dispersion of employment growth. However, unlike industry stock returns, industry employment likely responds to underlying reallocation shocks with a delay, especially when there are frictions in the labor market. Moreover, Abraham and Katz (1986) show that this variable is to a large extent driven by aggregate demand shocks.

specific returns for 49 industries as a proxy for sectoral labor reallocation shocks.[4]

To verify the validity of this proxy, we perform a battery of tests that link CSV to labor market conditions. First, we show that past industry idiosyncratic returns (measured with respect to the CAPM) help predict industry-level employment changes. Low performing industries tend to slightly lower their employment, while high performing industries significantly increase employment. However, when the need for labor reallocation across sectors is high (i.e., when CSV is high), winner industries no longer significantly increase their employment. This signals that they now face more labor market frictions. As human capital is to some extent tied to the industry (e.g., Katz and Summers, 1989; Neal, 1995), search and training costs are likely to be higher when hiring workers from a different industry compared to hiring from within the same industry. Second, when workers cannot instantly move from the losing to winning industries after a sectoral reallocation shock, aggregate unemployment increases. This is exactly what we find: CSV predicts significantly higher aggregate unemployment growth, in line with the sectoral shifts hypothesis of Lilien (1982). Third, we show that predictive power of CSV is even stronger for mismatch unemployment growth that is driven only by sectoral misalignment between unemployed workers and vacant job positions (Şahin et al., 2014). Furthermore, CSV strongly predicts Şahin et al.'s sectoral mismatch index that can be interpreted as an ex-post measure of sectoral labor reallocation needs. Fifth, alternative stock return dispersion measures based on individual stock returns or size book-to-market portfolios do not predict aggregate unemployment growth and have substantially lower or no predictive power for future stock market returns.[5] This suggests that the industry dimension of CSV and the link to future aggregate unemployment growth are essential for the predictive power of CSV for market returns.

The predictive power of CSV for future stock market returns is striking. Using monthly data between 1952:01 and 2019:12, we predict k-month ahead excess market returns, where $k = 1$, 3, 12, 24 and 36 months. We compare the predictive ability to twelve well-known variables, including three hiring-related variables from Chen and Zhang (2011) and the short interest index of Rapach

[4]Various papers use cross-sectional dispersion measures to proxy for resource mis- or reallocation. For example, David et al. (2019) use the dispersion in the marginal product of capital as a measure of misallocation.

[5]Goyal and Santa-Clara (2003) use the dispersion in individual stock returns as a proxy for idiosyncratic volatility. Maio (2015) uses return dispersion of 100 size and book-to-market (BM) ranked portfolios and links it to heterogeneous beliefs. Stivers and Sun (2010) find that the latter measure predicts the value premium and the momentum premium. Jorgensen et al. (2012) show that stock market returns help predict future dispersion in firm-level earnings growth.

et al. (2016).[6] First, we find that the predictive regression coefficient of CSV is always negative and significant. Second, the predictive power of CSV is substantially stronger than for the 12 alternative predictor variables; the in-sample and out-of-sample R^2s are considerably higher for one-quarter up to three-year ahead market returns in almost all cases.[7]. For instance, when predicting one-year ahead market returns, CSV has an out-of-sample R^2 of 12.56%, while those of the alternative variables range between -17.95% (log net payout yield) and 5.65% (short interest index). Finally, trading strategies based on CSV suggest that its predictive power is economically important as well.

To analyze the economic channel through which sectoral reallocation shocks affect future stock market returns, we propose a production-based asset pricing model with multiple industries. They are exposed to aggregate and industry-specific productivity shocks and adjust their workforce accordingly. The industry-specific shocks generate a need for sectoral labor reallocation, but also lead to variations in *per unit* labor adjustment costs. Specifically, following Weiss (1986) these adjustment costs are asymmetric hence preventing workers from declining industries from instantaneously moving to expanding industries. Furthermore, labor adjustment costs are time-varying depending on the dispersion in productivity shocks across industries.

With a reasonable choice of parameters, we demonstrate numerically that CSV is significantly negatively related to future excess stock market returns. Importantly, the only priced source of risk in our model is the shocks to aggregate productivity, which has a counter-cyclical price that is independent from variations in the sectoral reallocation shocks. The channel through which CSV generates return predictability is through time-varying industry exposures to aggregate productivity risk. In particular, when the need for sectoral reallocation is high (i.e., CSV is high), high productivity industries face higher labor adjustment costs than when CSV is low. As a result, they are less able to optimally adjust their workforce in response to aggregate economic fluctuations. This leads to lower aggregate risk exposures. Low productivity industries, on the other hand, face lower labor adjustment costs and their aggregate risk exposures do not vary much with CSV.[8] The

[6]The other alternative predictors are the log dividend-price ratio, the one-month T-bill rate, the log price-earnings ratio, the log net payout yield (Boudoukh et al., 2007), the default spread, the term spread, the inflation rate, and the consumption-wealth ratio (Lettau and Ludvigson, 2001).

[7]The only two exceptions are the short interest index which has a slightly higher out-of-sample R^2 at $k = 3$ (3.53% versus 3.40%), but not at other horizons k, and the term spread for $k = 36$ (15.16% versus 13.14%)

[8]We are not the first paper to link adjustment costs to aggregate risk exposures. In line with our finding that labor adjustment costs lower aggregate risk exposures, Qiu (2019) also argues for a negative impact and analyzes the

effect of the lower risk exposures of high productivity industries is amplified by their larger weight in the equity market portfolio. As a result, the exposure of the value-weighted equity market portfolio to aggregate productivity risk decreases when CSV is high. Our simulation results are consistent with this economic explanation: the exposure of value-weighted market portfolio to aggregate risk is negatively impacted by sectoral reallocation shocks.

Our model provides three new testable implications which we confirm in the data. First, the channel works mostly through high productivity (winning) industries who face higher labor adjustment costs. Accordingly, we find that CSV has much stronger predictive power for winning rather than losing industries, both in the model simulations and in the data. Second, as a consequence, the predictive power of CSV should be stronger for the value-weighted than for the equal weighted equity market portfolio. Again, this is supported in the model and in the data. Finally, the channel should only work for industries where labor adjustment costs are present to begin with. We use labor skill intensity at the industry level as a proxy for intrinsic labor adjustment costs and construct two labor skill-based CSV measures: high (low) skill CSV is based on the subset of industries that rely most on high (low) skilled labor. When we include both high skill CSV and low skill CSV in a predictive regression, only high skill CSV significantly predicts future market returns. In other words, consistent with the labor adjustment cost channel we show empirically that the predictive power of CSV depends on those industries that rely most on high skilled labor which is more costly to adjust.

We rule out three alternative explanations for the predictive power of CSV. We find in the data that it is not in line with a proxy for capital adjustment costs (Kim and Kung, 2017). We also show that the predictive power of CSV cannot be explained by slow information diffusion (using data on analyst coverage). Further, our predictability results at the industry level are inconsistent with investor over- or underreaction to industry-specific shocks.

Related Literature

Our paper relates to a growing literature on labor and asset pricing.[9] More specifically, several

consequences for firms' risk management in a corporate finance setting. Zhang (2005) and Cooper (2006) consider the impact of capital adjustment costs on aggregate risk exposures of value and growth firms. Kuehn et al. (2017) show that idiosyncratic productivity risk lowers the exposure to aggregate labor market tightness risk.

[9]For instance, Danthine and Donaldson (2002), Santos and Veronesi (2006), Chen and Zhang (2011), Eiling (2013), Berk and Walden (2013), Dittman, Palomino and Yang (2016), Donangelo et al. (2019), among many others.

studies consider the impact of labor market frictions on asset pricing, both in the time series as well as in the cross-section. This is done in settings with labor adjustment costs, search frictions or wage rigidity.

Merz and Yashiv (2007) first incorporate labor adjustment costs in the production-based asset pricing model of Cochrane (1991). Labor now becomes a "quasi-fixed" factor. Firms are compensated for the costs involved in hiring new workers and the resulting rents are included in the market value of the firm. This makes firms' hiring decisions forward looking, as argued by Belo et al. (2014). They show that hiring rates help predict firm-level stock returns in the cross-section. Belo et al. (2020) find that aggregate hiring rates have predictive power in the time series. Rather than analyzing labor adjustment costs in general, we focus on one specific source of labor adjustment costs: sectoral labor reallocation shocks. Various papers such as Lilien (1982), Şahin et al. (2014) and Kalay et al. (2018), show that this type of labor adjustment cost is economically relevant and affect long-term aggregate unemployment, which we confirm in the data. Moreover, while within-industry labor market frictions could also affect aggregate outcomes, Chodorow-Reich and Wieland (2019) and Nallareddy and Ogneva (2015) show that the between-industry frictions are key for generating realistic aggregate unemployment fluctuations.

Kuehn, Simutin and Wang (2017) propose a labor asset pricing model with a labor search and matching component. The efficiency of the matching technology (proxied by labor market tightness) is a source of priced risk, in addition to aggregate productivity shocks. In their model, idiosyncratic productivity risk lowers the exposure to aggregate labor market tightness risk. In our model, sectoral reallocation shocks (i.e., idiosyncratic productivity shocks) drive labor market frictions, but they are not a priced source of risk. Rather, the exposures to aggregate productivity risk are lower when there is more idiosyncratic productivity risk (and thus more labor adjustment costs). Another difference is that we focus on time series predictability while Kuehn et al. (2017) focus on the cross-section.

While in our model we consider labor market frictions that affect the quantity of labor, Favilukis and Lin (2016) consider a different type of friction that affects the price of labor: wage rigidity. Their model shows that sticky wages make dividends more volatile and hence increase risk for the firm.

Our paper also relates to studies on capital misallocation. For example, Ramey and Shapiro

(2001) empirically show that capital is strongly tied to the industry and that reallocating is costly. Kim and Kung (2017) propose an empirical measure of capital redeployability across industries. In a robustness test we condition CSV on this measure and find that the predictive power of CSV is not driven by capital adjustment costs that hinder capital reallocation across industries. Several studies focus on the amount of capital reallocation rather than reallocation shocks. For instance, Eisfelt and Rampini (2006) find that the amount of capital reallocation is procylical but the benefits (measured by the dispersion in capital productivity) are countercylical.[10] Hsieh and Klenow (2009) quantify the negative impact of capital and labor misallocation on aggregate manufacturing productivity. The model in Eberly and Wang (2009) shows how costly capital reallocation affects growth.

The paper is structured as follows. Section II discusses the data. Section III explains the construction of CSV and verifies its use as a proxy for sectoral reallocation shocks. Our key empirical results on the predictive power of CSV for future market returns are presented in Section IV. Section V presents a production-based asset pricing model along with calibration and simulation results and analysis of new testable implications from the model. Section VI discusses robustness tests, which are presented in a separate Internet Appendix. Section VII concludes. The Appendix provides details on the labor market data used and the computational algorithm used to numerically solve our model.

II Data

We use monthly returns on 49 industry portfolios in excess of the one-month T-bill rate to construct our main proxy for sectoral reallocation shocks, CSV. The data are from Kenneth French's website. The full sample period runs from January 1952 to December 2019, a total of 816 monthly observations. In addition, we evaluate the robustness of our results by performing our analysis over various subsample periods. As a proxy for the market portfolio we use monthly returns on the value-weighted CRSP market index. In robustness tests, we construct CSV based on monthly returns on 100 size and book-to-market ranked portfolios (also from French's website). Further, we construct CSV based on individual stock returns for all stocks traded on the NYSE, AMEX and Nasdaq from CRSP.

[10] Eisfelt and Rampini (2008) analyze the implications for managerial incentives.

We compare the performance of CSV to twelve alternative predictive variables that have been proposed in the literature. First, we use the log dividend-price ratio on the CRSP value-weighted market index (logDP), where dividends in a certain month are calculated as the sum of the past 12 months of dividends (following Fama and French, 1988). Next, we consider the yield on one-month T-bill relative to its previous 3-month moving average (RF). Third, we consider the cyclically adjusted log price-earnings ratio (logPE) from Robert Shiller's website. Fourth, we consider the log net payout yield (logNPY) from Boudoukh et al. (2007), which is provided by Michael Roberts. Fifth, we consider the default spread (DEF), calculated as the difference between the yield on Moody's Baa and Aaa rated corporate bonds. Next, we include the term spread (TERM), calculated as the yield difference between 10-year government bonds and 3-month T-bill rates. The seventh alternative predictor is the inflation rate (INFL), calculated as the log growth rate of the Consumer Price Index. The data for these latter three variables are from the Federal Reserve Bank in St. Louis. We also include the consumption-wealth ratio (CAY) from Lettau and Ludvigson (2001), which is provided by Martin Lettau. Following Vissing-Jørgensen and Attanasio (2003), we interpolate monthly values from quarterly values. This may give the monthly CAY measure some look-ahead bias, but as we will discuss later, it does not lead to an outperformance of this variable. In addition, we include three labor market related variables used by Chen and Zhang (2011): Payroll growth (PYRL), the Net hiring rate (NetHR) and the Net job creation rate in manufacturing (NetJC). As a final predictive variable we consider the short interest index (SII) of Rapach et al. (2016) from David Rapach's website. A number of alternative predictors are not available for the full sample period.[11] We perform the analysis for each variable based on the maximum number of observations available.

In addition, we use several labor market variables. Monthly aggregate US unemployment rates (UN) are from the Current Population Survey, provided by the Bureau of Labor Statistics (BLS). Following Loungani et al. (1990) we use a log transformation, where $un = \log(UN/(1 - UN))$. We also consider short term (0–5 weeks) and long term (27+ weeks) unemployment rates (BLS Table A-12). Industry-level employment data are from the Current Employment Statistics survey. Lastly, to measure labor skill, we combine data from the BLS Occupational Employment Statistics, the Census Current Population Survey – Merged Outgoing Rotation Group and the Dictionary

[11] The logNPY ends in December 2010, TERM starts in April 1953, CAY starts in April 1952 and ends in September 2013, NetHR starts in March 1977, NetJC ends in May 2005 and SII starts in January 1973.

of Occupational Titles. Further details about this labor market data (including the predictive variables from Chen and Zhang (2011)) can be found in Appendix A.

III Cross-Sectional Return Volatility and Sectoral Labor Reallocation

Following, among others, Loungani et al. (1990) and Brainard and Cutler (1993), we use the cross-sectional volatility (CSV) of industry-specific equity returns as a proxy for sectoral shifts. The idea is as follows. If certain industries are affected by adverse shocks while others are hit by positive shocks, the industry-specific returns presumably incorporate these shocks instantaneously. Hence, the cross-sectional dispersion of industry returns increases. The increase in CSV reflects the mismatch between taste and technology across industries and induces a need for labor reallocation.

Lilien (1982) considers the cross-sectional dispersion in industry unemployment growth as a proxy for sectoral shifts.[12] However, Abraham and Katz (1986) show that this measure is more driven by aggregate demand shocks than by sectoral reallocation shocks. The advantage of using the dispersion in industry-specific stock returns as a proxy is that we can take out aggregate demand shocks by considering industry idiosyncratic returns. Also, while sectoral shifts are typically reflected in employment data with a lag, stock returns are expected to respond instantaneously. Another advantage of using a stock-return based proxy is that data is available at high frequencies and with a long history. In Section III.B we verify the validity of our proxy by linking CSV to various labor market variables.

A. Construction of the CSV Measure

Our CSV measure is based on industry-specific returns of 49 industries. Using industry-specific rather than total industry returns removes the effect of aggregate shocks which do not increase the need for sectoral reallocation. Following Brainard and Cutler (1993), we first run the following regression using the data from the past 36 months:

$$R_{i,s} = \alpha_i + \beta_i R_{M,s} + \varepsilon_{i,s}, \quad s = t-35, \dots, t, \tag{1}$$

[12] Other employment-based measures are based on long term unemployment growth (Rissman, 1993) and the correlation between industry-level employment growth rates during and after a recession (Groshen and Potter, 2003).

where $R_{i,s}$ and $R_{M,s}$ are the month s excess returns of industry i and the market portfolio respectively, in excess of the 30-day T-bill rate. We then estimate the industry-specific returns for industry i at month s as its abnormal return from the CAPM, which is measured by

$$\eta_{i,s} = \hat{\alpha}_i + \hat{\varepsilon}_{i,s}, \tag{2}$$

where $\hat{\alpha}_i$ and $\hat{\varepsilon}_{i,s}$ are the OLS regression estimates of α_i and the fitted residuals obtained from (1). We then compute CSV at the end of month t as the cross-sectional standard deviation of the industry-specific returns from the past 12 months:[13]

$$CSV_t = \left[\frac{1}{48} \sum_{i=1}^{49} \left(\eta_{i,t-11:t} - \bar{\eta}_{t-11:t} \right)^2 \right]^{\frac{1}{2}}, \tag{3}$$

where

$$\eta_{i,t-11:t} = \prod_{s=t-11}^{t} (1 + \eta_{i,s}) - 1, \tag{4}$$

and

$$\bar{\eta}_{t-11:t} = \frac{1}{49} \sum_{i=1}^{49} \eta_{i,t-11:t}.$$

Our main CSV measure puts equal weights across the 49 industry-specific returns.[14] The impact of an industry-specific shock on the need for labor reallocation may depend on, for instance, the presence of unions in the industry (which makes layoffs more difficult), the presence of more industry-specific human capital (which makes labor less mobile), and the total employment in the industry (shocks in industries that are a large part of the labor market are expected to have a stronger effect on future aggregate unemployment). Most of these variables are unobserved, especially for a large cross-section of industries with a long history. While industry-level employment data is available, there are important limitations as discussed in Appendix A. Therefore, we use equal weights in our main CSV measure. Section V discusses a robustness test with employment-based weights.

[Insert Table I about here]

Table I reports summary statistics of CSV and the twelve alternative predictors for future equity market returns that we consider. CSV varies substantially over time; the average is 0.154 and the

[13] Sectoral reallocation shocks are permanent. Using a longer return horizon to calculate CSV helps to capture permanent shocks. In Section V, as a robustness test, we consider past 3-month and past 24-month industry-specific returns.

[14] At the beginning of the sample period, a few of the industry portfolios have missing returns, so the CSV is computed based on the industries with non-missing return data.

standard deviation is 0.043. The first and second order autocorrelation coefficients are 0.91 and 0.81 respectively, which is lower than those for most of the alternative predictors. The final column shows the correlation between the alternative predictors and CSV. Correlations are modest and range from -0.43 (log net payout yield) to 0.19 (logPE). This suggests that CSV captures a new aspect of equity return predictability compared to existing variables, which is confirmed by our empirical analysis in Section IV.

B. CSV as a Proxy for Sectoral Shifts

We verify that CSV proxies for sectoral labor reallocation in five different ways. First, we show that industry-specific stock returns predict industry-level employment changes. Second, we show that CSV predicts aggregate unemployment growth. Third, we use CSV to predict a direct measure of the mismatch between job seekers and job vacancies across industries. Fourth, CSV predicts the part of unemployment growth that can be attributed to the sectoral mismatch between job opportunities and job seekers. Finally, in the robustness section (Section VI) we show that modifications of the CSV measure that are less in line with the economic channel of sectoral shifts also weaken its predictive ability.

Table II shows the link between industry equity returns and subsequent employment changes at the industry level. This analysis helps us rule out the possibility that human capital and equity returns are inversely related, by which a positive shock to industry-level equity returns would decrease the demand for labor in the industry.

[Insert Table II about here]

To this end, we use industry-level employment data that are available for 35 industries. We construct 35 industry equity portfolios for matched industry codes using CRSP individual stock data. Each month, we sort industry equity portfolios into five quintiles, based on their past 12-month industry-specific returns. Then, we calculate the continuously compounded average employment growth for each quintile over the following k months. Throughout the paper we consider $k = 1$, 3, 12, 24 and 36 months. Table II Panel A shows the results. We can see that the "loser" industries with the lowest past equity returns decrease subsequent employment, while the "winner" industries increase subsequent employment. The employment changes for expanding industries are statistically significant. The difference between winners and losers (WML) is always statistically significant and positive. These results show a link between past industry equity returns and subsequent industry-level employment changes, confirming results in Brainard and Cutler (1993) and Shin (1997).

However, these findings by themselves do not yet indicate that aggregate unemployment increases, as the workers that are laid off in low performing industries could be the ones that are hired immediately in the top performing industries. Table II Panel B reports the same analysis, except that we condition on months in which CSV is in the top 10% of all values of CSV over the sample period. In other words, these are months when more workers need to move across industries. For these months when CSV is historically high, we calculate the average employment growth in subsequent months. The table shows that while loser industries now significantly reduce their workforce, winner industries no longer significantly increase employment, except for $k = 3$. In other words, during times when sectoral labor reallocation needs are particularly high (i.e., CSV is high), workers who are laid off are not immediately rehired. These findings signal the presence of labor market frictions (i.e., labor adjustment costs) that prevent high productivity industries from expanding their workforce. Arguably, search and trading costs are higher when recruiting new workers from other industries, i.e., firms face higher labor adjustment costs when CSV is high. A a consequence, aggregate unemployment increases, which we confirm next.

Figure 1 shows the time series of CSV as well as the time series of the aggregate unemployment rate (in levels). The shaded areas correspond to NBER recession dates.

[Insert Figure 1 about here]

We can see that CSV fluctuates substantially and while several peaks correspond to NBER recessions (e.g., 2008), others do not (e.g., 1966, 2016).

An expected consequence of sectoral labor reallocation shocks is an increase in future aggregate unemployment (e.g., Lilien, 1982; Şahin et al., 2014).[15] We explicitly test whether CSV has predictive power for aggregate unemployment changes. To this end, we run the following predictive

[15]The debate on the relative importance of sectoral reallocation versus aggregate demand shocks as drivers for unemployment is still ongoing (e.g., Groshen and Potter, 2003; Aaronson et al., 2004; Chodorow-Reich and Wieland, 2019 – for an overview, see Gallipoli and Pelloni, 2013). Overall, while the impact of aggregate demand shocks may not be completely ruled out, the evidence suggests that sectoral shifts are an important determinant of aggregate unemployment growth.

regression

$$\Delta un_{t:t+k} = un_{t+k} - un_t = b_0 + b_1 CSV_t + \varepsilon_{t:t+k}, \tag{5}$$

where $\Delta un_{t:t+k}$ is the log unemployment growth from the end of month t to month $t+k$, as defined in Section II. Table III Panel A reports the results.

[Insert Table III about here]

The table shows the OLS estimates of b_1, Newey-West (1987) adjusted t-ratios (based on $k-1$ lags) and the in-sample R^2s. Our analysis confirms the sectoral shifts hypothesis: an increase in CSV predicts higher future aggregate unemployment growth. In line with our expectations, the coefficient estimate is positive and significant for all values of k. Also, the final column reports the contemporaneous correlation between unemployment growth and continuously compounded excess market returns. The correlation is negative (and statistically significant for $k > 1$), confirming that the stock market tends to decline during periods of lower economic activity.

To further test the validity of CSV as a measure of sectoral reallocation shocks, we separately consider growth in short term unemployment rates (i.e., workers who are unemployed for a period between 0–5 weeks) and in long term unemployment rates (i.e., workers who are unemployed with a duration of more than 27 weeks). A key difference between the impact of aggregate demand shocks and sectoral shifts on unemployment growth is that the effect of aggregate demand shocks (i.e., business cycle changes) is temporary, while the effect of structural reallocation changes is permanent. Hence, we would expect long-term unemployment growth to be driven more by CSV, while short-term unemployment changes are more driven by aggregate demand shocks and less by CSV. This is confirmed by Panels B and C in Table III.[16]

The R^2s in Panel A do not exceed 4.50%, which suggests that besides sectoral shifts, other factors, including aggregate demand shocks, play a role in determining the aggregate unemployment. In our next analysis we therefore link CSV to unemployment measures that directly capture the misalignment of job seekers and job opportunities across sectors. To this end we first construct the mismatch index of Şahin et al. (2014), which measures the fraction of hires lost due to the job seeker misallocation across sectors. The mismatch index essentially is an ex-post measure of sectoral shifts. In contrast, CSV, which is based on industry returns, is an ex-ante measure of

[16] Blanchard and Diamond (1989), Brainard and Cutler (1993) and Loungani and Trehan (1997) show similar results.

sectoral shifts. We show that the two measures are strongly related. Table IV Panel A reports the results of the following predictive regression:

$$\mathcal{M}_{t+k} = b_0 + b_1 CSV_t + \varepsilon_{t+k}, \tag{6}$$

where $\mathcal{M}_{t+k}$ is the level of mismatch index at time $t+k$ assuming heterogeneity in labor productivity across industries, as discussed in Şahin et al. (2014). The analysis confirms the existence of a predictive relationship between CSV and the mismatch index. The coefficient associated with CSV is positive and significant for all k. Moreover, in terms of in-sample R^2, CSV demonstrates a strong predictive power with values up to 23% for $k = 12$.

[Insert Table IV about here]

Next, we examine if CSV can predict the component of the unemployment growth that is attributed to sectoral mismatch. Şahin et al. (2014) refer to this component as the mismatch unemployment. It is defined as the difference between the aggregate unemployment rate and a counterfactual unemployment rate where there is no impediment to the optimal allocation of job seekers across sectors. We repeat the exercise reported in Table III by replacing the aggregate unemployment rate with the mismatch unemployment rate. The results are reported in Table IV Panel B. We observe a considerable improvement in the predictive power of CSV for mismatch unemployment growth compared to aggregate unemployment growth. The coefficient associated with CSV is again positive and significant for all horizons but now the in-sample R^2 is much higher and ranges from 10.00% for $k = 36$ to 29.76% for $k = 12$.

In sum, the above findings show a strong link between CSV, future unemployment growth, future unemployment growth due to sectoral mismatch and an ex-post measure of sectoral shifts. These results validate CSV as a proxy for sectoral reallocation shocks.

IV Stock Market Return Predictability

We now turn to our main empirical analysis where we study the ability of CSV to predict future stock market returns.

A. Predictive Regressions

We start by running the following predictive regression of the k-month excess return on the market:

$$r_{t:t+k} = \alpha + \beta z_t + \varepsilon_{t:t+k}, \tag{7}$$

where $r_{t:t+k} = r_{t+1} + \cdots + r_{t+k}$ is the continuously compounded excess return of the market from the end of month t to month $t+k$, and z_t is the value of a predictive variable observed at the end of month t. We calculate standard errors of the OLS estimates of α and β, following Hodrick (1992) as well as following Newey-West (1987) with $k-1$ lags. We use $k = 1$, 3, 12, 24 and 36 months.

Next, we test for out-of-sample predictability, following among others, Campbell and Thompson (2008). Using all returns up to month t with a minimum of 20 years of monthly data, we estimate the above regression. Then, we use the estimated parameters to construct a forecast of the k-month excess return from month t to month $t+k$:

$$\hat{r}_{t:t+k} = \hat{\alpha}_t + \hat{\beta}_t z_t, \tag{8}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are estimated using data from the beginning of the sample period to month t. In addition to reporting the in-sample R^2, we also report the out-of-sample R^2 for the predictive regressions using the historical average excess market return (calculated over all months up to t) as a benchmark. The out-of-sample R^2 is calculated as:

$$R^2_{OOS} = 1 - \frac{\sum_{t=240}^{T-k}(r_{t:t+k} - \hat{r}_{t:t+k})^2}{\sum_{t=240}^{T-k}(r_{t:t+k} - k\bar{r}_{1:t})^2}, \tag{9}$$

where $\bar{r}_{1:t}$ is the average excess market return computed using data up to month t, and T is the length of the return series. The summation is over all months for which returns are forecasted (i.e., starting in month 241). Note that the out-of-sample R^2 can be negative in case the predictive variable has poor out-of-sample predictive ability.

[Insert Table V about here]

Table V reports the results. Each panel is based on a different horizon k. First, we see that CSV negatively predicts future market returns for all k, which is in line with the labor adjustment cost channel. For $k = 1$ and $k = 36$, the regression coefficient is statistically significant at the 5% level, for all other k it is significant at the 1% level.

The in-sample R^2s range from 0.78% for $k = 1$ to 17.92% for $k = 24$. The impressive performance of CSV extends to our out-of-sample analysis as well. Out-of-sample R^2s are all positive and range from 0.46% ($k = 1$) to 16.83% ($k = 24$). We should be careful however in comparing the results across different horizons k. For $k > 1$, longer horizon returns are partially overlapping. The increase in overlap for higher k could lead to an upward bias in the R^2. Hence, an increase of R^2 for higher k may simply be a statistical artifact rather than a sign of true improved performance. Therefore, in the following section we analyze trading strategies based on CSV. The utility gains from these trading strategies can be directly compared across horizons.

To put the predictive ability of CSV in perspective, we compare the performance of CSV to alternative predictive variables for a given k. The results are included in Table V. We compare CSV to 12 well-known predictive variables (see Section II for a description), including three labor market related variables proposed by Chen and Zhang (2011) and the short interest index (SII), which was proposed by Rapach et al. (2016) as "the strongest predictor of the equity risk premium identified to date." Given the impressive performance of SII, it poses the main hurdle for any new predictive variable.

Four alternative predictor variables have significant coefficient estimates for all k, at least at the 10% significance level and at least based on one of the two reported $t-$statistics: RF, TERM, INFL and CAY. However, across all k, the significance levels are not as high as for CSV. Some variables are (almost) never significant: NetHR, DEF, and logPE. LogNPY is insignificant for low k ($k = 1, 3$) while NetJC and SII are insignificant for higher k ($k = 24, 36$).

Next, we compare the in-sample and out-of-sample R^2s. When $k = 1$, the demeaned risk-free rate RF, PYRL and NetJC have somewhat higher in-sample R^2s compared to CSV. RF and SII have higher out-of-sample R^2s for $k = 1$. However, for $k > 1$, CSV shows an impressive outperformance compared to the existing predictive variables. The in-sample R^2 is always highest for CSV. For $k = 12$ and $k = 24$ CSV generates the highest out-of-sample R^2 as well. The differences are often remarkable. For example, when $k = 12$, CSV has an out-of-sample R^2 of 12.56%. The alternative variables have R^2s ranging from -17.95% (logNPY) to 5.65% (SII). For $k = 3$, only the SII has a slightly higher out-of-sample R^2 (3.53% versus 3.40%) and for $k = 36$ TERM has a somewhat higher out-of-sample R^2 (15.16% versus 13.14%). Note however, that most alternative predictors have negative out-of-sample R^2s meaning that the naive historical mean market return is even a better predictor out-of-sample than those variables. Their poor out-of-sample performance is consistent with findings of Welch and Goyal (2008).

Based on the above horse race, across all horizons, CSV easily outperforms the twelve alternative predictors. The significance levels of the coefficient estimate are the highest, the in-sample R^2 is always the highest for CSV and the out-of-sample R^2 is the highest for $k = 12$ and $k = 24$ and close to the highest for all other k. Note that this outperformance also holds compared to the short interest index proposed by Rapach et al. (2016). The correlation between the two variables is low at 0.14, which suggests that they capture different aspects of stock return predictability.

[Insert Table VI about here]

We further examine how CSV stacks up against other variables in predicting excess market return by running a series of multiple regressions in which we use a subset of predictors as independent variables. That is,

$$r_{t:t+k} = \alpha + \sum_{i \in S} \beta_i z_{i,t} + \varepsilon_{t:t+k}, \tag{10}$$

where S represents the index of the subset of predictors used in multiple regression and $z_{i,t}$ is the forecasting variable i observed at the end of month t. Panels A and B of Table VI show the in-sample and out-of-sample R^2s respectively for each specification. We start with a specification where all of the above mentioned alternative predictors are included. Except for $k = 1$, adding CSV to the set of predictors improves the predictive power in terms of both the in-sample and out-of-sample R^2s. Not surprisingly, the out-of-sample R^2s for such specifications with many predictors are negative due to overfitting. Therefore, we suggest two parsimonious specifications in which CSV and SII, or CSV and PYRL are used as independent variables. With CSV and SII we obtain an out-of-sample R^2 of as much as 23.07% for $k = 12$ ands a comparable value for $k = 24$. Using CSV and PYRL generates an out-of-sample R^2 of 16.59% for $k = 12$ and 20.44% for $k = 24$. We present the estimated values of the parameters as well as the in-sample and out-of-sample R^2s for the recommended regression including CVS, SII and PYRL in one multiple regression in Panel C. We obtain an impressive out-of-sample R^2 of 22.07% for $k = 12$. It is important to note that the coefficient associated with CSV is largely unchanged compared to the univariate regression and it remains significant in all of these specifications.

In summary, the results in Tables V and VI suggest that CSV is an important variable for forecasting market returns, both by itself as well as in the presence of other predictive variables previously proposed in the literature.

B. Trading Strategies

In order to assess whether the superior predictive performance of CSV can actually translate into higher utility for an investor, we construct trading strategies based on CSV. An additional advantage is that we can now directly compare the utility in terms of certainty equivalents across different horizons k. Following Rapach et al. (2010), we take the perspective of a mean-variance investor who allocates between the stock market portfolio and the risk-free asset. At each month t, the weight allocated to the market portfolio is determined by

$$\hat{w}_t = \frac{1}{\gamma} \frac{\hat{r}_{t:t+k}}{\hat{\sigma}^2_{t:t+k}}, \tag{11}$$

and $1 - \hat{w}_t$ is allocated to the risk-free asset. The coefficient of risk aversion is denoted by γ, for which we use a value of three following Rapach et al. (2010). $\hat{r}_{t:t+k}$ is the predicted k-month ahead continuously compounded excess market return at month t and is defined in (8). The forecast of the market excess return variance is denoted by $\hat{\sigma}^2_{t:t+k}$. We follow Campbell and Thompson (2008) and estimate it as k times the sample variance of the monthly excess market return over a rolling window of the past five years. As z_t we use our proxy for sectoral shifts (CSV) as well as the alternative predictors. To increase the power of our tests, the strategies that we examine include portfolios with overlapping periods when $k > 1$. Therefore, in any given month t, the strategies hold a series of portfolios that are selected in the current month as well as in the previous $k - 1$ months.

[Insert Table VII about here]

Table VII reports the results. Panel A shows, for different return horizons, the annualized sample mean and standard deviation of the excess return of portfolio strategies where CSV is used as the predictive variable. These are compared to a benchmark strategy where the market excess return is predicted using the historical monthly mean excess market return, i.e., $\bar{r}_{1:t}$. We find that the CSV-based trading strategies always lead to higher mean returns than the benchmark strategy, but also with slightly higher standard deviations (except for $k = 36$). For example, for $k = 12$, the CSV-based strategy leads to a mean return of 11.21% per annum and a standard deviation of 18.97%. In comparison, the benchmark strategy leads to a mean return of 5.44% and standard deviation of 16.23%.

To assess the economic and statistical significance of this outperformance and to compare a CSV-based strategy to strategies based on alternative predictors, we calculate the certainty equivalent (CE). The CE is calculated as

$$CE = \bar{R}_p - \frac{\gamma}{2}\hat{\sigma}_p^2, \tag{12}$$

where $\bar{R}_p$ and $\hat{\sigma}_p^2$ are the annualized sample mean and sample variance of the excess portfolio return associated with each trading strategy, calculated using the out-of-sample excess returns. We calculate the difference between the CE of the CSV-based trading strategy and the CE of the benchmark trading strategy, which is based on the historical mean. The CE difference provides a measure of additional risk-free return that the strategy earns compared to the benchmark strategy. Similarly, we calculate CE differences for strategies based on alternative predictors. We always use the historical mean-based strategy as a benchmark. To assess the statistical significance, we compute the t-ratio associated with the CE differences as derived in the Internet Appendix. Note that although the magnitude of the certainty equivalent depends on the coefficient of risk aversion (we use $\gamma = 3$), the t-ratio of the CE difference is independent of γ.

The results are reported in Panel B. The CSV-based strategy leads to a positive and significant CE difference for all horizons. The difference is economically important. For instance, for $k = 12$, the CSV-based strategy leads to an additional risk-free return of 4.32% per annum compared to the benchmark strategy. The CE differences are statistically significant at the 10% level for $k = 1$, at the 5% level for $k = 3$, and at the 1% level for $k = 12$, 24, and 36.[17] As we can directly compare CE across different horizons k, we conclude that the predictive power of CSV is economically most important for one-quarter to one-year ahead market returns.

In comparison, except for the term spread, none of the alternative predictors not show any CE differences that are positive and significant. Often, the estimated difference is negative, suggesting the strategy underperforms the benchmark strategy. The only exception is the strategy based on the term spread for $k = 24$ and 36.

In sum, the strong predictive power of CSV for future market returns shown in predictive

[17] Note that this is a one-sided test.

regressions is also economically meaningful. When using CSV in out-of-sample trading strategies, the portfolio performance is significantly improved.

V A Production-Based Asset Pricing Model

To better understand the mechanism through which sectoral shifts generate stock return predictability, we propose a production-based asset pricing model with sectoral reallocation shocks and time-varying labor adjustment costs that generate a link between CSV and future market returns. Our model belongs to the class of models that incorporate labor adjustment costs in a neoclassical framework, such as Merz and Yashiv (2007) and Belo et al. (2014).

A. Model Setup

Our setup is as follows. We assume that the economy consists of N industries, each of which is represented by a single representative firm. At the beginning of period t, each firm (industry) faces two types of productivity shocks: x_t, which is the aggregate productivity shock affecting all industries, and $z_{i,t}$, which is the idiosyncratic productivity shock affecting only industry i. We define $z_{i,t}$ as the product of two random variables:

$$z_{i,t} = S_t \cdot \tilde{z}_{i,t}, \tag{13}$$

where $S_t > 0$ represents sectoral labor reallocation shocks and therefore drives the cross-sectional dispersion in industry productivity. Each firm generates operating profits $Y_{i,t}$ according to a non-increasing return-to-scale production function

$$Y_{i,t} = e^{(x_t + z_{i,t})} N_{i,t}^{\alpha}, \quad 0 < \alpha \leq 1, \tag{14}$$

where α is the labor share in production and $N_{i,t}$ is the size of the firm's workforce. We define $s_t = \log(S_t)$ as the log of the reallocation shocks. The dynamics of $N_{i,t}$ are determined by the firms' optimal hiring decisions. We assume that a firm's workforce has the following law of motion

$$N_{i,t+1} = (1 - \delta) N_{i,t} + H_{i,t}, \tag{15}$$

where δ is the total separation rate and $H_{i,t}$ is the net number of hires during period t.

If firms could adjust their workforce without costs, workers would instantly move from low to high productivity industries. However, this contrasts our empirical results in Section III where high productivity industries do not expand their workforce when the need for sectoral reallocation is high. We therefore assume that adjusting the workforce is costly, due to for instance search and training costs, or disruptions to the production process as a result of layoffs. Similar to, among others, Merz and Yashiv (2007), Chen and Zhang (2011) and Belo et al. (2014), we assume that firms face labor adjustment costs. Consistent with the labor search literature we assume that total labor adjustment costs $C_{i,t}$ have a quadratic functional form:

$$C_{i,t} = \frac{c_{i,t}}{2}\left(\frac{H_{i,t}}{N_{i,t}}\right)^2 N_{i,t}.$$

This specification has the desired property of being convex and increasing in the number of new hires and decreasing in the size of the firm's workforce, as suggested by intuition. While in Chen and Zhang (2011) the per-unit labor adjustment costs are constant, in our model they are asymmetric and vary over time and across industries. Specifically, the per unit adjustment costs are specified as

$$c_{i,t} = \kappa S_t * \Phi(\tilde{z}_{i,t}); \tag{16}$$

where $\Phi(\cdot)$ is the standard normal CDF function. We specify κ as a constant parameter that captures the intrinsic labor adjustment costs for hiring and layoffs. For example, high skilled workers are likely more costly to hire (i.e., more training and search costs), resulting in a higher κ. We will explore the impact of these so-called intrinsic labor adjustment costs in Section V.F where we analyze further testable implications from the model.

Per unit labor adjustment costs are asymmetric as they are a function of the normalized industry-specific productivity shock; $\Phi(\tilde{z}_{i,t})$ is higher for top performing industries that look to hire more workers after having received positive idiosyncratic productivity shocks, than for under-performing industries that tend to lay off workers. On aggregate, when hiring is more expensive than firing, workers who are laid off in losing industries will not be re-hired in winning industries instantaneously. As a result, future unemployment increases, which is the key mechanism of the sectoral shifts hypothesis (Lilien, 1982). Weiss (1986) emphasizes the importance of allowing for industry-specific productivity shocks and asymmetric labor adjustment costs when modelling the impact of sectoral shifts on future aggregate unemployment.

Furthermore, the per unit adjustment costs are time-varying and increasing in S_t. As mentioned earlier, a positive shock to S_t implies a higher dispersion across industries in terms of idiosyncratic productivity shocks, and potentially a higher need for the reallocation of labor across sectors. The labor adjustment costs firms face when hiring new workers limit worker mobility from contracting to expanding industries. A possible micro foundation for this is industry specificity of human capital. This in turn increases the hiring costs, mainly due to higher search costs resulting from a tighter labor market in high productivity industries, as well as higher training costs when hiring from a pool of workers with unmatched skills.

Assuming that firms are purely equity financed, the firm's dividend will be equal to

$$D_{i,t} = Y_{i,t} - W_{i,t}N_{i,t} - \frac{c_{i,t}}{2}\left(\frac{H_{i,t}}{N_{i,t}}\right)^2 N_{i,t}, \tag{17}$$

The wage rate is denoted by $W_{i,t}$ and is specified as a function of aggregate productivity

$$W_{i,t} = e^{\tau x_t} \tag{18}$$

Similar to Belo et al. (2014), the wage rate is a function of aggregate productivity to reflect cyclicality in wages.

B. Dynamics

We assume that the aggregate and standardized idiosyncratic productivity shocks follow AR(1) processes as

$$x_t = \rho_x x_{t-1} + \sigma_x \epsilon_t^x, \tag{19}$$

$$\tilde{z}_{i,t} = \rho_{\tilde{z}} \tilde{z}_{i,t-1} + \sigma_{\tilde{z}} \epsilon_{i,t}^{\tilde{z}}, \tag{20}$$

where ϵ_t^x and $\epsilon_{i,t}^{\tilde{z}}$ are i.i.d. standard normal random variables, and they are independent of each other. We impose $\sigma_{\tilde{z}} = \sqrt{1-\rho_{\tilde{z}}^2}$ to guarantee that the unconditional variance of $\tilde{z}_{i,t}$ is equal to one. The log of the reallocation shocks s_t evolves as an AR(1) process:

$$s_t = \rho_s s_{t-1} + \sigma_s \epsilon_t^s, \tag{21}$$

where ϵ_t^s is i.i.d. standard normal, and independent of ϵ_t^x and $\epsilon_{i,t}^{\tilde{z}}$. This in turn implies that the cross-sectional standard deviation of the idiosyncratic productivity shocks $z_{i,t}$ is proportional to S_t.

C. Asset Prices

Following Berk et al. (1999) and Zhang (2005), we specify an exogenous pricing kernel without explicitly modeling the consumer's problem. We assume that only aggregate productivity shocks are priced. The log of the stochastic discount factor is specified as

$$\log M_{t+1} = \log\beta + \gamma_t(x_t - x_{t+1}), \tag{22}$$

in which $0 < \beta < 1$ is the time discount factor, and γ_t is the counter-cyclical price of risk, defined, following Zhang (2005), as

$$\gamma_t = \gamma_0 + \gamma_1(x_t - \bar{x}), \tag{23}$$

Risk premia follow naturally as

$$E_t(R_{i,t+1}) = R_f - R_f Cov_t(R_{i,t+1}, M_{t+1}) \tag{24}$$

where R_f is the risk free rate. As the price of risk in our model is independent from the sectoral reallocation shocks, any predictive power of sectoral reallocation shocks for future excess stock returns comes from time varying exposure to the priced aggregate productivity risk factor.

Our choice of a one factor pricing kernel with the aggregate productivity as the only determinant of the price of risk is intended to maintain consistency with our focus on the production side of the economy. Effectively, it serves our purpose to pin down the effect of labor adjustment costs as the channel that induces return predictability while shutting down alternative consumption-based channels that potentially generate return predictability through time series variations in the price of risk. In the following section, we show that labor adjustment costs lower the exposure to aggregate productivity risk and hence lead to lower risk premia. We acknowledge, however, that this simplifying assumption for the pricing kernel can potentially lead to the failure of our model to precisely capture a number of the empirical regularities that are documented in the literature but are outside of the scope of this study.

D. Optimization

Each period, firms choose the number of workers to hire with a goal to maximize their discounted future cash flows, i.e., $D_t + E_t[\sum_{j=1}^{\infty} M_{t+j} D_{i,t+j}]$, where M_{t+j} is the stochastic discount factor at time $t+j$. As a result, we can write the firms' maximization problem as

$$\max_{H_{i,t+j},N_{i,t+j+1}} E_t \left[D_{i,t} + \sum_{j=1}^{\infty} M_{t+j} \left[f(x_{t+j}, z_{i,t+j}) N_{i,t+j}^{\alpha} - W_{i,t+j} N_{i,t+j} - \frac{c_{i,t+j}}{2} \left(\frac{H_{i,t+j}}{N_{i,t+j}} \right)^2 N_{i,t+j} \right] \right] \tag{25}$$

subject to (15).

We obtain the firm's optimal hiring decision by numerically solving this optimization problem. As such, the firms' optimal hiring decisions are used to determine the corresponding optimal dividend and market value, which are in turn the determinants of the firm (industry) stock returns.

E. Model Calibration and Simulation Results

We solve the firm's optimization problem numerically by applying the value function iteration procedure on a discritized state space. A detailed explanation of this procedure is provided in Appendix B. We simulate 100 panels each containing 50 industries and 900 months. Using the firm's optimal hiring and dividend policies, we extract firm (i.e., industry) returns which aggregate to market returns. We can now construct CSV using the procedure described in Section III.A. We test the predictive relationship between CSV and excess market returns using simulated data.

E.1. Calibration of Parameters

Our benchmark model is calibrated according to the values reported in Table VIII. We adhere to the literature in our calibration of the parameters that have been given a value in existing studies. For additional free parameters we make our choices in such a way to achieve an approximate match between the aggregate moments generated by our model and those implied by historical data.

[Insert Table VIII about here]

We start with the output elasticity of labor, α, which is set to 0.7 following Kuehn et al. (2017).Their choice of this parameter is based on the assumption that labor is the only production factor, which is an assumption that we make in our model as well. We set the exogenous separation rate to $\delta = 3\%$, roughly the same as the separation rate identified by Davis et al. (2006) and Kuehn et al (2017). This includes only the rates associated with voluntary separations by workers due to various reasons such as preferable working conditions or career development. The wage rate sensitivity to aggregate productivity shocks is determined by the parameter τ. Following Belo et al. (2014), we set this parameter with the objective to match the annual volatility of the Hodrick-Prescott filtered aggregate wage rate per worker (1.4%).

We next calibrate κ, which is the intrinsic labor adjustment cost that determines the total labor adjustment cost incurred by the firm. We set this parameter at 200 with the aim to match the net hiring rate of 3.5% from JOLTS, calculated as the difference between gross hiring rate and layoffs rate. Using a quadratic specification for the adjustment cost as ours, Belo et al. (2020) estimate the per-unit labor adjustment cost to be between 200 and 300. While in our setting a quadratic adjustment cost function is adopted as well, there is asymmetry in per-unit labor adjustment costs.

The next set of parameters are those that are related to prices of assets. The parameter $\beta = 0.997$ is set to match the average risk-free rate, while $\gamma_0 = 2.3$ and $\gamma_1 = -2.76$ are adopted from the values estimated by Belo et al. (2020) while making sure that the resulting equity premium is close that implied by the data when levered by the average debt-to-equity ratio of 0.67. Next, we set $\rho_x = 0.95$ and $\sigma_x = 0.0137$ following among others Bai (2016). The values of $\rho_{\tilde{z}} = 0.965$ is chosen following Kuehn et al. (2017), while $\sigma_{\tilde{z}} = 0.262$ is set to make the standard deviation of $\tilde{z}_{i,t}$ equal to one.

We also set $\sigma_s = 0.1$ to obtain a volatility for idiosyncratic productivity shock that is equal to 0.1, which is used by Zhang (2005) and Kuehn et al. (2017). Since the persistence associated with the reallocation shocks is not directly observable, we set it in such a way to provide us with correlation for the CSV that is as close to that implied by the data as possible. To this end we set $\rho_s = 0.96$.

We verify our calibration by comparing a set of moments based on artificial data generated by the calibrated model with those implied by the data. The results are reported in Table IX. Overall, the model does a reasonable job at generating aggregate moments close to the values suggested by the data, implying that the calibrated model captures important dynamics of the stock market.[18]In addition, our simulations show a correlation of 76% between the reallocation shocks S_t and CSV. This supports our argument in Section V.A where the implicit assumption was that the predictive relationship between S_t and excess market returns implies a predictive relationship between CSV

[18]Note that the observed mismatch between some of the moments generated by our model and those derived from the actual data can be due to our simplifying assumption for the price of risk.

and excess market returns.

[Insert Table IX about here]

E.2. CSV and Future Stock Returns

In order to assess the extent to which we capture the effect of labor adjustment costs in our model, we run a predictive regression of market excess returns on CSV based on artificial data. To this end, we follow the procedure outlined in Section IV.A for $k = 1$, 3, 12, 24 and 36. We define the market return as the value-weighted average of the industry stock returns. The results are provided in Table X.

[Insert Table X about here]

The simulation-based results are in line with our empirical findings. The coefficient associated with CSV is negative over all horizons. The coefficient estimate is statistically significant for 3, 12, 24 and 36-month horizons. The magnitudes of the coefficients and the R^2s in our simulated tests are smaller than those of the empirical analysis. A potential explanation is that CSV is more volatile in our calibrated model compared to the data.

E.3. Mechanism: Aggregate Risk Exposures

In our model, the price of risk is independent from the reallocation shocks. Rather, the predictive power of reallocation shocks for excess stock market returns is driven by time-varying exposures to priced aggregate productivity risk. The negative slope coefficient in the predictive regressions shows that when CSV is high, the equity market risk premium declines. This implies that the exposure of the value-weighted equity market portfolio to aggregate productivity risk declines when there is a greater need for sectoral labor reallocation.

[Insert Table XI about here]

Table XI Panel A indeed shows that the conditional covariance between the value-weighted equity market returns and the stochastic discount factor is less negative when reallocation risk is high (i.e., S_t is high) than when it is low. In other words, when S_t is high (and consequently, CSV is high), the value-weighted equity market portfolio is less exposed to aggregate productivity risk.

To uncover the exact mechanism, we look at the impact of labor adjustment costs on aggregate risk exposures. When firms face higher labor adjustment costs, their dividends are smoother making them less sensitive to aggregate economic fluctuations. This is in line with studies such as Zhang (2005) and Cooper (2006) who link capital adjustment costs to lower aggregate risk exposures. In our model, labor adjustment costs are not only time-varying and increasing in S_t, they are also asymmetric and are higher for industries that receive high industry-specific productivity shocks. These industries should therefore be less exposed to aggregate risk than the low productivity industries where labor adjustment costs play a smaller role.

[Insert Table XII about here]

Table XII Panel A shows the conditional covariances between industry returns and the stochastic discount factor for low and high productivity industries. The results show that while the exposure of low productivity industries does not vary with S_t, high productivity industries are less exposed when S_t is high. This pushes down their conditional expected returns, which is what we see in Panel B.

Summarizing, due to higher labor adjustment costs that especially high productivity industries face when S_t is high, their optimal hiring policy would comprise regions of hiring inactivity. This, in turn, makes their dividends less sensitive to aggregate productivity shocks. In the value-weighted equity market portfolio, these high productivity industries have a larger weight, which implies that the exposure of the value-weighed equity market portfolio to aggregate risk is also lower when S_t is high.

F. New testable implications from the model

Our model provides us with three new testable implications. First, the predictive power of CSV should be stronger for the value-weighted than for the equal-weighted market portfolio. Second, it should be stronger for high productivity industries where labor adjustment costs play a larger role than for low productivity industries. Third, it should be stronger when focusing on industries for which labor is intrinsically more costly to adjust. As we discuss below, we confirm all three implications in the simulations and in the data.

F.1. Predicting Value- versus Equal-Weighted Equity Market Returns

In our model, the impact of sectoral reallocation shocks on labor adjustment costs and aggregate risk exposures is most pronounced for the high productivity industries that face higher labor adjustment costs. The relatively larger weight of these industries in the value-weighted market portfolio commands a lower exposure to aggregate productivity shocks for the overall market portfolio. A direct implication of this is that the effect on the equal weighted market portfolio should be smaller. Indeed, Table XI Panel B shows that the relationship between the market portfolio's covariance with the stochastic discount factor and S_t is substantially weaker for the equal-weighted market portfolio compared to value-weighted portfolio. This is further confirmed in Table XIII Panel A, which reports the simulation results from a predictive regression using equal- rather than value-weighted market portfolio.

[Insert Table XIII about here]

Lowering the weight of the high productivity industries with greater market capitalization in the market portfolio makes the overall market portfolio less exposed to aggregate productivity shocks, leading to a weaker predictive relationship between CSV and market portfolio. Panel B of Table XIII confirms this for actual data as well. For instance, when predicting 12-month ahead equal weighted excess market returns, the out-of-sample R^2 is -0.57% while Table V shows an R^2 of 12.56% for value-weighted market returns.

F.2. Predicting Industry Equity Returns

Another implication of our model is that the predictive power of CSV should be stronger for high productivity industries as they face more adjustment costs and hence have cash flows that are less sensitive to aggregate productivity shocks (as shown in Table XII). To test this empirically, we proxy unobserved industry-specific productivity shocks by past industry-specific idiosyncratic stock returns, similar to Table II. We expect a higher coefficient associated with CSV and a higher R^2 for the outperforming industries compared to other industries.

We test this model prediction by first creating quintile portfolios from our set of industries based on their past performance. Specifically, each month, we sort industries into quintiles based on their past 12-month idiosyncratic returns (estimated using Equation (4)). Then, for each quintile, we calculate the equally weighted excess return across industries over the following k months. This gives us a time-series of returns for each of the quintile portfolios (i.e., past losers, 2, 3, 4 and past winners). Next, we use CSV to predict the continuously compounded excess returns on each of these five quintiles. This is similar to (7), except that we use the quintile industry excess returns as the dependent variable instead of market excess return.

The results in Table XIV support this hypothesis. Panel A shows the test results based on simulated data. While industries in all performance quintiles have a negative CSV coefficient, the coefficient associated with the winner industry is significantly more negative compared to those in the loser industry. In other words, higher industry-level labor adjustment costs are associated with higher CSV coefficient in this predictive regression. This model prediction is validated when we perform this test on actual data shown in Panel B. Here, the coefficient estimate of CSV for past winners is again larger in magnitude than that of past losers in all cases. Further, past winners have higher in- and out-of-sample R^2s than past losers.[19]

[Insert Table XIV about here]

F.3. Intrinsic Labor Adjustment Costs: High versus Low Skill Labor

We focus on the impact of labor adjustment costs resulting from sectoral reallocation shocks on risk exposures as the main mechanism of the predictive relationship between CSV and future stock market returns.

The impact of sectoral reallocation shocks on labor adjustment costs for an industry is influenced by certain characteristics of the type of labor employed that determine the difficulty with which the industry can make adjustments in its labor force. In our model, we capture these so-called intrinsic labor adjustment costs by the parameter κ.

For two industries facing similar industry-specific productivity, a positive sectoral reallocation shock would lead to a proportionally higher per-unit labor adjustment for the industry that has a greater κ. This implies that we should expect a more significant predictive relationship between

[19] We also use CSV to predict industry returns for each of the 49 individual industry portfolios separately. The results for $k = 12$ are reported in the Internet Appendix. We find that CSV predicts industry returns with a negative sign for 47 out of 49 industries. The coefficient estimate is statistically significant for 22 or 33 industries (based on either the Hodrick (1992) or Newey-West (1987) adjusted t-ratios respectively) and most industries have substantial in-sample R^2s. More than half of the industries have positive out-of-sample R^2s.

the CSV and market excess return when κ is larger.

To test this empirically, we focus on one characteristic of labor that likely affects the intrinsic adjustment costs: skill. Filling vacancies for high skilled workers is expected to be costlier than filling vacancies for low skilled workers. As a result, a higher CSV would imply higher labor adjustment costs only when the type of labor employed in the industry is more difficult to replace.

To this end, we classify occupations into high and low skill based on the level of Specific Vocational Training (SVP) index required for the job, extracted from the Dictionary of Occupational Titles (DOT). This index serves as a proxy for the level of skill required for each occupation. Following Belo et al. (2017), we consider an occupation as being high skilled if the value of SVP is greater than six (corresponding to occupations requiring over two years of preparation), and low skilled otherwise. We define industry-level skill following Belo et al. (2017) as the percentage employment in high skill occupations in the industry, based on the occupational employment composition of industries from the Bureau of Labor Statistics OES dataset. We also construct an alternative skill measure based on the ratio of total wages paid to the high skilled workers relative to the total wage expenditure in the industry. This is in line with the notion that wages better reflect the extent to which an industry depends on its skilled workers in the production process. Next, we identify the High Skill (HS) and Low Skill (LS) industries each year as those that belong to the highest and lowest terciles of industries in terms of the industry skill measure. We then construct CSV for each set of industries using the procedure explained in Section II.A with industries being ranked each year in June.

[Insert Table XV about here]

Table XV shows the results of the predictive regression for future excess stock market returns using CSV_{HS}, which is the CSV constructed based on the High-Skill industries, and CSV_{LS} which is based on the Low-Skill industries. Since the labor skill data becomes available in 1990, we can perform this part of our analysis only in-sample. Panel A presents the results when the industry-level skill measure is defined based on the percentage of high-skilled workers in the industry. Consistent with our hypothesis, we observe that the predictive power of CSV is concentrated among industries that predominantly depend on high skill workers, i.e., industries that are likely to face higher labor adjustment costs. The predictive regression using CSV_{HS} generates a coefficient that is negative and statistically significant for all horizons. In sharp contrast, the coefficient associated with the

CSV_{LS} is not significantly different from zero when CSV_{HS} is also included in the predictive regression. When CSV_{LS} is included as the only predictive variable, the coefficient is marginally significant for $k = 3, 12$, and 36. For all k, we find that the in-sample R^2 is substantially higher for CSV_{HS} than for CSV_{LS}. For example, for $k = 12$, CSV_{HS} leads to an R^2 of 17.99%, while that of CSV_{LS} is only 6.65%. Panel B shows similar results for $k > 3$ when we define the industry-level skill measure as the percentage of wages associated with high skill worker.

Overall, we subdivide the industries into industries that rely most on high skilled labor, which is intrinsically costly to adjust, versus those that rely more on low skilled labor. When we create CSV measures for these two subsets of industries, we find that only high skill CSV predicts market returns. This is in line with costly labor adjustment as a potential channel behind the observed predictive relationship between CSV and future market returns.

Summarizing, we incorporate sectoral shifts in a production-based asset pricing model by allowing for time-varying and asymmetric labor adjustment costs. We show that this generates a link between CSV and future stock returns in the model though time-varying aggregate risk exposures. More labor adjustment costs dampen the impact of aggregate economic fluctuations and lower the risk exposures. We present three new testable implications from the model that are all supported by the data.

VI Further Discussion

A. Alternative Explanations

We examine three alternative explanations for the negative predictive power of CSV for future market returns. First, we test whether capital adjustment costs rather than labor adjustment costs are the first-order impediment for firms to respond to sectoral reallocation shocks. Firms can face adjustment costs when trying to increase their capital stock, and this can reduce their investment returns and hence stock returns. We investigate this alternative explanation by applying a similar approach as in the previous section where we conditioned CSV on a measure of labor skill. We now condition CSV on a measure for the difficulty at which an industry can make adjustments to its capital stock. Industries that rely on highly industry-specific physical assets are expected to find it more costly to adjust their capital, especially when the need for the reallocation of capital is high due to sectoral reallocation shocks. On the other hand, industries that mostly rely on assets that can be redeployed across a wide range of industries should experience a less severe increase in their capital adjustment costs during these periods. Therefore, under this alternative explanation, we expect that the predictive power of CSV would diminish by the extent to which industries rely on redeployable assets. We test this hypothesis using the industry-level asset redeployability index constructed by Kim and Kung (2017) as a measure of the industries' ability to obtain physical capital from other industries. Hence, this measure is negatively related to the industries' intrinsic capital adjustment cost. In each month, we construct CSV_{HR} as the CSV that is based on industries that belong to the highest tercile of industries in terms of their redeployability index. Similarly, we construct CSV_{LR} using industries in the lowest tercile in terms of redeployability index.[20]

[Insert Table XVI]

Table XVI compares the predictive power of the CSV constructed using high-redeployability industries with that of the low-redeployability industries. Due to the shorter time period over which asset redeployability data is available, we focus on in-sample predictive regressions. Panel A reports the results when the asset-level redeployability score is constructed using industry market capitalization as weights, while Panel B shows the results when the score is simply based on the number of industries that use the asset. The results do not show a notable difference between the predictive power of the CSVs based on the two types of industries when we include either CSV_{HR} or CSV_{LR} in the predictive regression. When we include both in one predictive regression, we find that CSV_{HR} tends to have more significant coefficients. Recall that high redeployability implies low capital adjustment costs. These results therefore contradict the alternative hypothesis that capital adjustment costs generate the predictive power of CSV for future market returns. The results in Gavazza (2011) provide a possible rationale for this finding. If firms optimally hold on to their most industry-specific assets in response to adverse profitability shocks, they can simply adjust the capacity utilization of their assets in place in response to sectoral reallocation shocks. This makes their capital adjustment costs less sensitive to sectoral reallocation shocks.

Second, we investigate the role of investor over- or underreaction to industry-specific shocks.

[20] We define industries using the same BEA-based industry classification used Kim and Kung (2017). We exclude industries that consist of fewer than five firms at each time to alleviate the effect of firm-specific shocks on CSV, and to maintain a high correlation between the CSV based on the BEA industry classification and the one based on 49 Fama-French industry classification.

If investors overreact to good news in expanding industries, or they underreact to bad news in declining industries at time t, the returns presumably will be corrected one period later. Hence, according to this hypothesis, at time $t+1$ both expanding and contracting industries experience lower returns, which may drive the negative response of the market at $t+1$. An important implication of the over- or underreaction hypothesis is that only extreme industries will respond at time $t+1$, as opposed to all industries. However, our results in Table XIV Panel B show that CSV negatively predicts future equity returns for virtually all industries, not just a few extreme past winners or past loser industries. As a result, the over- or underreaction does not seem to be a plausible explanation for the observed return predictability.

A third alternative explanation is based on slow information diffusion. According to the sectoral shifts hypothesis, sectoral shocks signal lower future economic activity. In order to assess the full extent of the sectoral reallocation that these shocks bring about and the effect on future aggregate unemployment, investors need to consider all industries. However, investors often specialize in one or a few industries only (Hong et al., 2007). If information diffuses slowly across industries, the full effect of the sectoral reallocation shocks will be incorporated in other industry returns and in market returns with a delay. However, our finding that the predictability is significant even for long horizons (up to three years) is challenging for a slow information diffusion explanation.[21] Further, when we interact CSV with an aggregate measure of analyst coverage,[22] we do not find that the predictive ability of CSV increases during times when analyst coverage is lower. These results contrast a slow information diffusion explanation.

B. Robustness Tests

Below we discuss various robustness tests, which are reported in the Internet Appendix.

CSV based on different horizons

First, our results are robust when using past three-month and past 24-month (rather than past 12-month) industry idiosyncratic returns to calculate CSV. Similar to our main measure, these two

[21] The cross-asset predictability identified by among others, Hong et al. (2007), Cohen and Frazzini (2008) and Menzley and Ozbas (2010) is typically confined to the one-year horizon.

[22] We construct a monthly measure of average analyst coverage for the firms in each industry. We then take the equally weighted average of the analyst coverage of the top and bottom 20 percentile of industries ranked in terms of past 12 months idiosyncratic return. Results are reported in the Internet Appendix.

alternative CSV measures negatively predict lower future excess market returns. At the same time, significance of the coefficients and the in-sample and out-of-sample R^2s are generally somewhat lower than for the 12-month CSV. Further, they also positively predict unemployment growth with a significant coefficient for $k = 1, 3$, and 12.

CSV based on different weighting schemes

Second, we use different weighting schemes to calculate CSV. Our main measure equally weights all industries. As a first alternative, we use employment-based weights. This is in line with our economic interpretation of CSV as a proxy for sectoral shifts. When an industry is hit by a shock, the subsequent need for labor reallocation is expected to be higher when that industry has a large share of the labor market. Unfortunately, detailed industry-level employment data at a monthly frequency for a long sample period are not available. We use employment data for 35 industries (see Appendix A), ending in April 2003. We construct value-weighted industry equity portfolios for matched industries using individual stock returns from the CRSP. Consistent with our base results, the employment weighted CSV predicts future equity market returns with a negative sign. The coefficient estimate is significant for all $k > 1$. The equally weighted CSV has stronger predictive power, which may stem from the fact that these 35 industries are less well balanced. Unreported results show that the average employment share varies from 0.12% (tobacco) to 23.89% (services). Also, we should keep in mind that other factors may play a role as well, such as the presence of unions and the specificity of human capital in the industry. Further, when the employment weighted CSV measure is based on past 3-month returns, it significantly predicts future unemployment growth.

Our second alternative weighting scheme uses market capitalization-based weights. Note that there is less economic reason to weight sectoral reallocation shocks by the equity market capitalization of the industry. In fact, employment-based weights can be quite different from value weights. For instance, unreported results show that the average employment-based weight of retail trade is 17.56%, while the average value weight is only 5.13%. We use the original set of 49 industry equity portfolios over the full sample period to construct CSV with value weights. Similar to the equally weighted CSV, the value-weighted CSV significantly predicts future stock market returns with a negative sign. However, for $k > 1$ the in-sample and out-of-sample R^2s are lower compared to our main results based on the equally weighted CSV. Further, the value-weighted CSV has predictive ability for future unemployment growth, but here again, the results are somewhat weaker than for the equally weighted CSV. In sum, while our results on stock market predictability are robust to using market capitalization based weights, the equally weighted CSV is a better proxy for sectoral shifts and has stronger predictive ability for market returns.

CSV based on total industry returns

Several existing papers use cross-sectional return dispersion measures to forecast market returns (e.g., Goyal and Santa-Clara, 2003, Garcia et al., 2014). They typically find that their measures, which are interpreted as proxies for aggregate idiosyncratic risk, positively predict future market returns. There are two main differences with our empirical measure. First, we use idiosyncratic returns rather than total returns. Second, we use industry returns rather than individual stock returns. To further compare our results to these papers, we first construct CSV based on total industry returns. A CSV measure based on total returns is a less suitable proxy for sectoral reallocation shocks, because total returns are affected by aggregate demand shocks as well. Using idiosyncratic returns allows us to control for these aggregate demand shocks. Indeed, CSV based on total industry returns does not significantly predict future unemployment growth. It still has predictive power for future stock market returns, but in contrast to Goyal and Santa-Clara (2003) and Garcia et al. (2014), the sign is always negative. This is consistent with our main analysis.

CSV based on individual stock returns

Next, we use individual stocks to construct CSV. To be more comparable with existing papers, we again use total returns in this analysis. We use both equal weights and market capitalization based weights. These indivual stock return CSV measures have little predictive ability for future equity market returns. Some coefficients are significant, but out-of-sample R^2s are almost all negative or they are close to zero. Importantly, the coefficient estimate is always negative, similar to our base results. The lack of significant positive coefficients is in line with Bali et al. (2005) and Wei and Zhang (2005). Further, we find that these alternative CSV measures predict lower rather than higher unemployment growth which contrasts the sectoral shifts hypothesis.

CSV based on other portfolio returns

In our next robustness test, we use idiosyncratic returns on 100 size and book-to-market ranked portfolios to construct CSV, similar to Maio (2015). We find that it predicts future market returns with a negative sign, but the industry-based CSV measure outperforms for $k > 1$. Moreover, the resulting CSV measure fails to predict unemployment growth.

The above analyses highlight that the industry dimension of return dispersion measures is a key driver of their predictive power for future stock market returns. The robustness tests also show that using a better proxy for sectoral shifts (with more economic motivation) leads to better predictability of equity returns and aggregate unemployment growth. This is in line with our proposed economic channel through which CSV predicts equity market returns, namely sectoral labor reallocation.

Sub sample periods

Finally, we perform our analysis for three separate subsample periods. First, we start in January 1973 (rather than 1952), which is comparable to many existing studies on return predictability. We find an even stronger link between CSV and future stock market returns with higher in-sample and out-of-sample R^2s than for the full sample period. Also, the predictive power of CSV for future unemployment growth is substantially stronger over this period. Next, we split our sample in two halves: from January 1952 to December 1985 and from January 1986 to December 2019. The corresponding results confirm that the strongest predictive power for both stock market returns and unemployment growth occurs in the later part of the sample period. This part of our sample period includes the 1991–1992 and 2001 crises, during which sectoral shifts played an important role according to Groshen and Potter (2003).

To put these findings in perspective, it is important to note that the relative importance of sectoral reallocation shocks compared to aggregate demand shocks as a driver for unemployment likely changes over time. During times when labor is more mobile or when the economy is doing well, the effect of reallocation shocks is expected to be weaker (e.g., Davis, 1987).

VII Conclusion

This paper proposes a new variable that helps predict future stock market returns: the cross-sectional volatility of industry-specific stock returns (CSV). We find that increases in CSV strongly and robustly predict lower future market returns. Importantly, the predictive ability translates into significant utility improvements when we use CSV in a trading strategy. In addition, CSV substantially outperforms a large number of well-known alternative predictors of stock market returns.

CSV has a clear economic interpretation. Following, among others, Loungani et al. (1990) and Brainard and Cutler (1993), we show that CSV serves as a proxy for sectoral labor reallocation shocks. As such, it can be linked to time-varying labor adjustment costs. When the cross-sectional dispersion in industry returns is large, there is a greater need for reallocation of workers from low performing to high performing industries. Due to limited labor mobility (for instance, as a result of industry-specific human capital), reallocation takes time and resources. In other words, labor adjustment costs increase. We propose a production-based asset pricing model in which sectoral reallocation shocks increase labor adjustment costs. These higher adjustment costs affect the firm's ability to respond to aggregate economic fluctuations and hence dampen the aggregate risk exposure leading to a lower risk premium. Consistent with this economic mechanism, we find that the predictive ability of CSV depends on those industries that rely the most on high skilled labor, which is costlier to adjust.

Appendix

A. Labor market data

Our list of alternative predictive variables includes, among others, three labor market variables from Chen and Zhang (2011): payroll growth (PYRL), the Net hiring rate (NetHR) and the Net job creation rate in manufacturing (NetJC). PYRL is defined as the log growth rate of the monthly seasonally adjusted total nonfarm payrolls of all employees, from the BLS. NetHR is defined as the gross hiring rate minus separation rate. We obtain the data from 1977Q1 to 2002Q4 from Merz and Yashiv (2007). Starting 2001Q1 we use data from the Jobs Opening and Labor Turnover Survey (JOLTS). We follow Chen and Zhang (2011) and scale the second series using the ratio between the average of the series during the overlapping period, i.e., 2001−2002. NetJC is defined as the difference between the job creation rates and job destruction rates from John Haltiwanger's website. We convert the two quarterly variables into monthly values by setting the values each month equal to the most recent value available in that month.

Part of the analysis uses monthly industry-level employment data for a set of 35 industries from the Current Employment Statistics survey. We use total nonfarm payroll employees per industry. In 2003, the CES industry classification changes. As there is no one-to-one match between the old and the new industry classification, we end our sample for this part of our analysis in May 2003. All employment data are seasonally adjusted.

For the sectoral mismatch index and mismatch unemployment rate, we follow the procedure proposed by Şahin et al. (2014) and construct the time series of the two variables for the period between January 2001 and December 2019. The codes for these two variables and the series themselves are available on the AEA website up to 2011. We update the data until the end of our sample period in December 2019.

In our test for the link between market return predictability and the level of labor skill, we combine three datasets. First, the BLS Occupational Employment Statistics (OES) tracks employment across industries for each occupation in the economy from 1988 onwards. Following Donangelo (2014), for each year prior to 1996, we combine data from the previous three years to ensure continuity in industry coverage in our data. This restricts our sample period for this test to 1990 and after. The dataset also contains median hourly wage estimates for each industry-occupation starting in 1997. Prior to 1997, we obtain average hourly wage estimates from the Census Current Population Survey – Merged Outgoing Rotation Group (CPS-MORG).[23] Next, the resulting dataset is matched with the Dictionary of Occupational Titles (DOT), which contains score for attributes of a wide range of occupations in the economy. To this end, we link each nine-digit DOT occupation code with the occupation codes used in the OES using the 2000 Standard Occupation Code (SOC) as the reference occupation classification. We use the crosswalk tables provided by the National Crosswalk Service Center and the mapping tables used by Belo et al. (2017).

B. Computational Algorithm

We start by discretizing the state space (x, $\tilde{z}$, s) into a grid consisting of nine grid points for x, seven grid points for z, and seven grid points for s. To this end, we utilize Rouwenhorst's (1995) method by which the states follow a Markov chain with finite states. We use this method in our simulation because each of the above processes have a persistence level greater than 0.9. We also specify a grid consisting of 50 points for the labor stock N with lower bound $\underline{N} = 0.01$ and upper bound $\bar{N}$=100. The distance between grid points is determined using the recursive procedure suggested by McGrattan (1999). Similarly, for the choice variable N', which represents the optimal employment $N_{i,t+1}$ in Equation (15), we specify a log-linear grid of 5000 over the same interval.

We solve the firm's maximization problem (25) on each grid point using the value function iteration procedure. Having obtained the optimal policies over each grid point, we construct a simulated path for each state variable for a panel of 50 firms, each representing an industry. We find the value functions and the corresponding hiring decisions on the simulation paths that are off the grid points using linear interpolation. We first neutralize the effect of the initial conditions defined for the state variables by running a simulation over 10,000 months, by which we obtain the stationary cross-sectional distribution of the idiosyncratic productivity shocks and that of the optimal values of the choice variables. The end values generated by this procedure are then fed as the initial values to our main simulation procedure, in which firm (industry) stock returns are calculated based on the optimal dividend and the firm value over 900 months.

[23] For each industry-occupation in the OES we use the corresponding earnings-weighted average hourly wage of individuals aged 18 to 65 in its matching broad industry-occupation observations in CPS-MORG. For the industry-occupations with no CPS-MORG match, we use the nationwide hourly wage for that occupation. We follow the BLS regarding industry classifications and use two-digit SIC codes until 2001 and three-digit NAICS codes afterwards.

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Table I: **Summary Statistics**

The table reports summary statistics for 13 potential predictors of market returns. CSV is the equally weighted cross-sectional volatility of 49 industry returns, based on the continuously compounded past 12-month industry idiosyncratic returns, where industry idiosyncratic returns are calculated as the sum of the intercept and residuals of the CAPM, estimated over the past 36 months. The other twelve predictors are: the log dividend-price ratio (logDP), the one-month T-bill rate, which is demeaned by its three-month moving average (RF), the log price earnings ratio (logPE), the log net payout yield (logNPY), the default premium (DEF), calculated as the difference between the yields on Baa and Aaa rated corporate bonds, the term spread (TERM), calculated as the difference between the yields of 10-year government bonds and three-month Treasury bills, the inflation rate (INFL), based on the change in the consumer price index (all items, urban), the consumption-wealth ratio (CAY), payroll growth (PYRL), net hiring rate (NetHR), net job creation in manufacturing (NetJC), and short interest (SII). All data are at the monthly frequency. The sample period covers January 1952 to December 2019 but six predictors are available for a shorter sample period: logNPY ends in December 2010, TERM starts in April 1953, CAY starts in April 1952 and ends in September 2013, SII starts in January 1973, NetHR starts in March 1977, and NetJC ends in May 2005. The table reports the mean, median, standard deviation, first and second order autocorrelation coefficients (AR(1) and AR(2)), the minimum and maximum values of each predictor and its correlation with CSV (corr. CSV).

	Mean	Median	Std. Dev.	AR(1)	AR(2)	min	max	corr. CSV
CSV	0.154	0.144	0.043	0.905	0.812	0.076	0.390	1.000
logDP	−3.575	−3.531	0.384	0.991	0.981	−4.546	−2.843	−0.277
RF	0.00%	0.00%	0.063%	0.407	0.029	−0.483%	0.423%	−0.041
logPE	2.909	2.964	0.403	0.995	0.988	1.893	3.789	0.193
logNPY	−2.196	−2.144	0.211	0.980	0.963	−3.235	−1.700	−0.428
DEF	0.97%	0.86%	0.43%	0.970	0.922	0.32%	3.38%	0.110
TERM	1.46%	1.43%	1.17%	0.958	0.896	−2.65%	4.42%	−0.115
INFL	0.28%	0.24%	0.31%	0.616	0.480	−1.79%	1.79%	0.140
CAY	0.03%	0.06%	1.77%	0.991	0.973	−3.88%	3.44%	−0.120
PYRL	0.14%	0.15%	0.25%	0.485	0.533	−1.21%	1.61%	−0.108
NetHR	0.17%	0.10%	0.34%	0.841	0.682	−0.50%	1.50%	−0.076
NetJC	−0.22%	−0.07%	1.22%	0.899	0.798	−4.22%	4.60%	−0.224
SII	0.000	0.031	1.000	0.972	0.952	−2.394	2.845	0.135

Table II: **Industry Stock Returns and Future Industry-level Employment Changes**

This table shows a link between industry-level equity returns and industry-level employment changes. Each month, we sort 35 portfolios into quintiles based on their past 12-month industry-specific returns. Then, we record the industry-level employment growth for these industries for the following k months, calculated as the continuously compounded average employment growth over all industries within the quintile. The sample period is from January 1952 to April 2003. Panel A reports an unconditional analysis and Panel B conditions on months in which CSV is in the top 10% (taken over the full sample period). Below the average industry-level employment changes, we report the corresponding Newey-West (1987) adjusted t-ratios based on $k-1$ lags. The final column WML reports the difference between the top quintile (past winners) and bottom quintile (past losers). ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Unconditional Analysis

		Loser	2	3	4	Winner	WML
$k=1$	ΔEmpl. (%)	−0.05	−0.04	0.06	0.05	0.13	0.17
	t-ratio	(−0.73)	(−0.92)	(1.78)*	(1.76)*	(3.68)***	(2.56)**
$k=3$	ΔEmpl. (%)	−0.20	−0.09	0.21	0.14	0.30	0.50
	t-ratio	(−1.16)	(−0.79)	(2.38)**	(1.84)*	(3.94)***	(3.15)***
$k=12$	ΔEmpl. (%)	−0.66	−0.02	0.36	0.50	0.86	1.52
	t-ratio	(−1.26)	(−0.04)	(0.90)	(1.45)	(2.50)**	(4.15)***
$k=24$	ΔEmpl. (%)	−0.91	0.11	0.53	0.97	1.30	2.21
	t-ratio	(−0.99)	(0.16)	(0.78)	(1.57)	(1.96)**	(3.78)***
$k=36$	ΔEmpl. (%)	−0.68	0.61	1.25	1.53	1.40	2.08
	t-ratio	(−0.56)	(0.66)	(1.40)	(1.68)*	(1.51)	(2.52)**

Panel B: Conditioning on CSV Being in the Top 10%

		Loser	2	3	4	Winner	WML
$k=1$	ΔEmpl. (%)	0.09	−0.17	−0.04	−0.12	0.02	−0.06
	t-ratio	(0.25)	(−2.44)**	(−0.74)	(−1.21)	(0.19)	(−0.17)
$k=3$	ΔEmpl. (%)	−0.29	−0.57	−0.24	−0.32	0.50	0.78
	t-ratio	(−0.37)	(−2.18)**	(−0.97)	(−1.17)	(2.16)**	(0.99)
$k=12$	ΔEmpl. (%)	−1.95	−1.68	−1.25	−0.79	0.47	2.43
	t-ratio	(−1.69)*	(−1.61)	(−1.04)	(−0.74)	(0.47)	(2.45)**
$k=24$	ΔEmpl. (%)	−3.47	−2.49	−1.85	−1.03	−0.34	3.13
	t-ratio	(−2.08)**	(−1.34)	(−0.88)	(−0.57)	(−0.22)	(3.44)***
$k=36$	ΔEmpl. (%)	−3.52	−1.59	−0.07	0.10	0.17	3.69
	t-ratio	(−1.32)	(−0.70)	(−0.03)	(0.04)	(0.09)	(1.36)

Table III: **Predicting Aggregate Unemployment Growth Using CSV**

This table reports results of the following predictive regression of k-month ahead aggregate unemployment growth on CSV,

$$\Delta un_{t:t+k} = b_0 + b_1 CSV_t + \varepsilon_{t:t+k},$$

where $\Delta un_{t:t+k} = un_{t+k} - un_t$, and un_t is based on a log transformation of the unemployment rate: $un_t = \log(UN_t/(1 - UN_t))$. The second column ($\hat{b}_1$) reports estimates of b_1 and the next column (t-ratio) gives the Newey-West (1987) adjusted t-ratios of $\hat{b}_1$, based on $k - 1$ lags. The fourth column presents the regression's in-sample R^2 and the final column reports the correlation between the log excess stock market returns and unemployment growth, where both are taken over the same k-month horizon. Panel A is based on total unemployment, while Panels B and C are based on long term (27+ weeks) and short term (0–5 weeks) unemployment respectively. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Predicting Aggregate Unemployment Growth				
k	$\hat{b}_1$	t-ratio	R^2_{IS}	$\text{corr}(r_{M,t:t+k}, \Delta un_{t:t+k})$
1	0.080	(2.59)**	0.89%	−0.027
3	0.226	(2.29)**	1.75%	−0.077**
12	0.833	(1.80)*	3.11%	−0.251***
24	1.422	(2.20)**	4.50%	−0.396***
36	1.402	(1.80)*	3.25%	−0.500***
Panel B: Predicting Long Term Unemployment Growth (27+ weeks)				
k	$\hat{b}_1$	t-ratio	R^2_{IS}	$\text{corr}(r_{M,t:t+k}, \Delta un_{t:t+k})$
1	0.230	(3.05)***	1.22%	−0.010
3	0.583	(3.00)***	2.51%	0.053
12	2.081	(2.18)**	4.12%	0.003
24	3.539	(2.35)**	5.25%	−0.186***
36	3.971	(2.15)**	4.92%	−0.338***
Panel C: Predicting Short Term Unemployment Growth (0–5 weeks)				
k	$\hat{b}_1$	t-ratio	R^2_{IS}	$\text{corr}(r_{M,t:t+k}, \Delta un_{t:t+k})$
1	0.014	(0.25)	0.01%	0.004
3	0.074	(0.99)	0.20%	−0.095***
12	0.161	(0.79)	0.33%	−0.338***
24	0.234	(0.83)	0.53%	−0.408***
36	0.126	(0.41)	0.13%	−0.415***

Table IV: **Predicting Sectoral Mismatch Index and Mismatch Unemployment Growth Using CSV**

This table reports results of predictive regression for labor market-based proxies of the sectoral mismatch between unemployed workers and job vacancies. Panel A reports the result of the following predictive regression

$$\mathcal{M}_{t+k} = b_0 + b_1 CSV_t + \varepsilon_t,$$

where $\mathcal{M}_{t+k}$ is the sectoral mismatch index based industries with heterogenous productivity. Panel B reports the results of the following predictive regression of k-month ahead mismatch unemployment growth on CSV,

$$\Delta un_{\mathcal{M},t:t+k} = b_0 + b_1 CSV_t + \varepsilon_{t:t+k},$$

where $\Delta un_{\mathcal{M},t:t+k} = un_{\mathcal{M},t+k} - un_{\mathcal{M},t}$, and $un_{\mathcal{M},t}$ is based on a log transformation of the mismatch unemployment rate: $un_{\mathcal{M},t} = \log(UN_{\mathcal{M},t}/(1 - UN_{\mathcal{M},t}))$. The second column ($\hat{b}_1$) reports estimates of b_1 and the next column (t-ratio) gives the Newey-West (1987) adjusted t-ratios of $\hat{b}_1$, based on 12 lags for Panel A, and $k-1$ lags for Panel B. The fourth column presents the regression's in-sample R^2. The sample period covers January 2001 to December 2019. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Predicting Sectoral Mismatch Index			
k	$\hat{b}_1$	t-ratio	R^2_{IS}
1	0.039	(1.94)*	3.13%
3	0.039	(1.76)*	3.17%
12	0.097	(3.48)***	23.00%
24	0.059	(2.90)***	8.72%
36	0.048	(1.83)*	5.29%
Panel B: Predicting Sectoral Mismatch Unemployment			
k	$\hat{b}_1$	t-ratio	R^2_{IS}
1	0.573	(3.19)***	12.25%
3	1.232	(2.46)**	12.61%
12	4.086	(4.74)***	29.76%
24	4.719	(3.56)***	18.48%
36	4.201	(1.94)*	10.00%

Table V: **Predicting Stock Market Returns Using CSV and Alternative Predictors**

The table reports results of the following predictive regression:

$$r_{t:t+k} = \alpha + \beta z_t + \varepsilon_{t:t+k},$$

where $r_{t:t+k}$ is the continuously compounded k-month excess return on the market from month t to month $t+k$. We estimate predictive regressions for the following predictive variables (z_t): the proxy for sectoral shifts (CSV), the log dividend price ratio (logDP), the de-meaned risk-free rate (RF), the log price earnings ratio (logPE), the log net payout yield (logNPY), the default spread (DEF), term spread (TERM), inflation rate (INFL), the consumption-wealth ratio (CAY), payroll growth (PYRL), net hiring rate (NetHR), net job creation in manufacturing (NetJC), and short interest index (SII). The sample period covers January 1952 to December 2019 but five predictors are available for a shorter sample period: logNPY ends in December 2010, TERM starts in April 1953, CAY starts in April 1952 and ends in September 2013, SII starts in January 1973, NetHR starts in March 1977, and NetJC ends in May 2005. The table reports the regression coefficient estimate ($\hat{\beta}$), the corresponding t-ratios of Hodrick (1992) and Newey-West (1987) with $k-1$ lags, as well as the in-sample and out-of-sample R^2s. The five panels show results for $k = 1, 3, 12, 24$ and 36 months. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: $k = 1$

	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
CSV	−0.087	(−2.30)**	(−2.33)**	0.78%	0.46%
logDP	0.007	(1.58)	(1.60)	0.37%	−0.61%
RF	−0.074	(−2.27)**	(−2.44)**	1.2%	0.66%
logPE	−0.004	(−1.05)	(−1.05)	0.17%	−1.09%
logNPY	0.011	(1.18)	(1.21)	0.3%	−1.46%
DEF	0.003	(0.70)	(0.70)	0.09%	−0.59%
TERM	0.003	(1.94)*	(1.95)*	0.55%	−0.65%
INFL	−0.013	(−2.18)**	(−2.15)**	0.85%	−0.47%
CAY	0.002	(1.77)*	(1.78)*	0.38%	−0.08%
PYRL	−0.584	(−0.88)	(−0.89)	0.12%	−0.15%
NetHR	−0.575	(−1.19)	(−1.19)	0.19%	−0.15%
NetJC	−0.378	(−2.97)***	(−3.14)***	1.14%	0.05%
SII	−0.004	(−1.80)*	(−1.83)*	0.62%	1.04%

Table V: **Predicting Stock Market Returns Using CSV and Alternative Predictors – *continued***

Panel B: $k = 3$					
	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
CSV	−0.360	(−3.06)***	(−3.93)***	4.07%	3.40%
logDP	0.022	(1.73)*	(2.12)**	1.19%	−1.79%
RF	−0.118	(−1.94)*	(−1.99)**	0.94%	0.39%
logPE	−0.014	(−1.15)	(−1.40)	0.54%	−3.11%
logNPY	0.032	(1.13)	(1.46)	0.73%	−4.1%
DEF	0.010	(0.80)	(0.82)	0.32%	−2.18%
TERM	0.008	(1.81)*	(2.05)**	1.29%	−1.71%
INFL	−0.028	(−1.74)*	(−1.80)*	1.28%	−1.69%
CAY	0.005	(2.00)**	(2.20)**	1.33%	−0.24%
PYRL	−2.625	(−1.66)*	(−1.57)	0.73%	−0.15%
NetHR	−0.034	(−0.03)	(−0.03)	0.00%	−0.78%
NetJC	−1.005	(−2.73)***	(−3.03)***	2.50%	−0.32%
SII	−0.012	(−1.91)*	(−2.06)**	2.04%	3.53%

Panel C: $k = 12$					
	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
CSV	−1.311	(−3.08)***	(−4.43)***	12.52%	12.56%
logDP	0.092	(1.85)*	(2.16)**	4.80%	−11.74%
RF	−0.266	(−2.31)**	(−2.08)**	1.12%	−1.45%
logPE	−0.067	(−1.39)	(−1.67)*	2.82%	−12.59%
logNPY	0.178	(1.68)*	(2.20)**	5.03%	−17.95%
DEF	0.039	(0.98)	(1.19)	1.11%	−3.51%
TERM	0.034	(2.20)**	(2.65)***	5.80%	1.26%
INFL	−0.109	(−2.11)**	(−2.62)***	4.44%	−0.13%
CAY	0.020	(1.85)*	(2.02)**	4.32%	−0.80%
PYRL	−14.051	(−2.84)***	(−3.10)***	4.89%	0.79%
NetHR	−6.008	(−1.24)	(−1.62)	1.66%	−7.36%
NetJC	−3.416	(−2.66)***	(−2.43)**	6.85%	0.29%
SII	−0.042	(−1.68)*	(−1.90)*	5.91%	5.65%

Table V: **Predicting Stock Market Returns Using CSV and Alternative Predictors – *continued***

Panel D: $k = 24$					
	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
CSV	−2.140	(−3.00)***	(−4.44)***	17.92%	16.83%
logDP	0.166	(1.71)*	(2.00)**	8.37%	−29.86%
RF	−0.241	(−1.51)	(−1.70)*	0.49%	−1.51%
logPE	−0.126	(−1.31)	(−1.62)	5.18%	−28.17%
logNPY	0.366	(1.84)*	(2.79)***	11.67%	−25.58%
DEF	0.036	(0.52)	(0.75)	0.51%	−4.45%
TERM	0.051	(1.97)**	(3.04)***	7.26%	12.34%
INFL	−0.134	(−1.47)	(−3.15)***	3.59%	0.81%
CAY	0.034	(1.60)	(1.93)*	7.16%	−0.75%
PYRL	−15.909	(−2.04)**	(−2.36)**	3.39%	1.16%
NetHR	−1.726	(−0.23)	(−0.27)	0.08%	−6.18%
NetJC	−1.467	(−0.77)	(−0.75)	0.70%	−0.82%
SII	−0.050	(−1.02)	(−1.45)	4.39%	5.49%

Panel E: $k = 36$					
	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
CSV	−2.349	(−2.55)**	(−3.68)***	15.90%	13.14%
logDP	0.204	(1.43)	(1.91)*	9.46%	−41.09%
RF	−0.202	(−1.11)	(−1.79)*	0.26%	0.98%
logPE	−0.165	(−1.14)	(−1.59)	6.55%	−36.18%
logNPY	0.407	(1.45)	(2.71)***	10.92%	−29.16%
DEF	0.035	(0.37)	(0.57)	0.37%	−18.43%
TERM	0.074	(2.18)**	(3.86)***	11.99%	15.16%
INFL	−0.151	(−1.26)	(−3.59)***	3.39%	0.68%
CAY	0.043	(1.37)	(1.72)*	8.70%	−7.09%
PYRL	−16.540	(−1.69)*	(−2.74)***	2.76%	2.41%
NetHR	−1.202	(−0.11)	(−0.13)	0.03%	−5.84%
NetJC	−0.412	(−0.19)	(−0.20)	0.04%	1.17%
SII	−0.046	(−0.62)	(−1.05)	2.66%	3.85%

Table VI: **Predicting Stock Market Returns Using Multiple Regressions**

The table reports results of the following predictive regression:

$$r_{t:t+k} = \alpha + \sum_{i \in S} \beta_i z_{i,t} + \varepsilon_{t:t+k},$$

where $r_{t:t+k}$ is the continuously compounded k-month excess return on the market from month t to month $t+k$ and S represents the index of the subset of variables used as forecasting variables in the predictive regression. For each specification, we select regressors from the following set of predictive variables ($z_{i,t}$): the proxy for sectoral shifts (CSV), the log dividend price ratio (logDP), the demeaned risk-free rate (RF), the log price earnings ratio (logPE), the log net payout yield (logNPY), the default spread (DEF), term spread (TERM), inflation rate (INFL), and the consumption-wealth ratio (CAY), payroll growth (PYRL), net hiring rate (NetHR), net job creation in manufacturing (NetJC), and short interest index (SII). The sample period covers January 1952 to December 2019 but three predictors are available for a shorter sample period: logNPY ends in December 2010, TERM starts in April 1953, CAY starts in April 1952 and ends in September 2013, SII starts in January 1973, NetHR starts in March 1977, and NetJC ends in May 2005. For each specification, we restrict the sample period to the longest period that is available for all independent variables used in that specification. Panel A reports the in-sample R^2 for each specification and each forecasting horizon. Panel B presents out-of-sample R^2 for each specification and each forecasting horizon. Panel C reports the regression coefficient estimate ($\hat{\beta}$), the corresponding t-ratios of Hodrick (1992) and Newey-West (1987) with $k-1$ lags, as well as the in-sample and out-of-sample R^2s for two recommended specifications, in which the forecasting variables are CSV and TERM, or CSV and PYRL. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table VI: **Predicting Stock Market Returns Using Multiple Regressions** – ***continued***

Panel A: In-Sample R^2					
	$k=1$	$k=3$	$k=12$	$k=24$	$k=36$
All ex. CSV	4.48%	7.29%	25.34%	42.18%	53.08%
All with CSV	4.48%	9.38%	32.41%	60.16%	63.73%
[CSV, SII]	1.24%	5.60%	19.14%	22.58%	18.81%
[CSV, PYRL]	0.97%	5.24%	19.34%	23.30%	20.40%
[CSV, PYRL, SII]	1.50%	7.30%	25.09%	27.21%	23.65%

Panel B: Out-of-Sample R^2					
	$k=1$	$k=3$	$k=12$	$k=24$	$k=36$
All ex. CSV	−7.73%	−30.99%	−63.89%	−65.97%	−104.47%
All with CSV	−10.08%	−27.06%	−43.36%	4.59%	−59.61%
[CSV, SII]	1.61%	8.96%	23.07%	23.99%	17.17%
[CSV, PYRL]	0.41%	3.89%	16.59%	20.44%	17.03%
[CSV, PYRL, SII]	0.69%	6.89%	22.07%	26.47%	20.70%

Panel C: Recommended Specifications

		Specification: [CSV, PYRL, SII]				
k		CSV	PYRL	SI	R^2_{IS}	R^2_{OOS}
1	$\hat{\beta}$	−0.088	−1.204	−0.003	1.50%	0.69%
	t-ratio$_{Hodr}$	(−1.92)*	(−0.95)	(−1.75)*		
	t-ratio$_{NW}$	(−1.93)*	(−0.96)	(−1.78)*		
3	$\hat{\beta}$	−0.375	−5.498	−0.011	7.30%	6.89%
	t-ratio$_{Hodr}$	(−2.69)***	(−1.76)*	(−1.90)*		
	t-ratio$_{NW}$	(−3.75)***	(−1.78)*	(−2.15)**		
12	$\hat{\beta}$	−1.464	−20.882	−0.043	25.09%	22.07%
	t-ratio$_{Hodr}$	(−2.95)***	(−2.30)**	(−1.75)*		
	t-ratio$_{NW}$	(−5.00)***	(−3.43)***	(−2.09)**		
24	$\hat{\beta}$	−2.161	−23.843	−0.051	27.21%	26.47%
	t-ratio$_{Hodr}$	(−2.66)***	(−1.73)*	(−1.06)		
	t-ratio$_{NW}$	(−3.70)***	(−2.47)**	(−1.41)		
36	$\hat{\beta}$	−2.383	−27.893	−0.054	23.65%	20.7%
	t-ratio$_{Hodr}$	(−2.24)**	(−1.59)	(−0.74)		
	t-ratio$_{NW}$	(−2.89)***	(−2.57)**	(−1.18)		

Table VII: **Trading Strategies based on CSV and Alternative Predictors**

The table reports the economic value of predictive power of CSV when used as a predictive variable in a trading strategy, following Rapach et al. (2010). The realized gain is calculated from the perspective of a mean-variance investor who allocates between the market portfolio and the risk-free asset. At each time t, the weight allocated to the market portfolio is

$$\hat{w}_t = \frac{1}{\gamma} \frac{\hat{r}_{t:t+k}}{\hat{\sigma}^2_{t:t+k}}.$$

and $1 - \hat{w}_t$ is allocated to the risk-free asset, where γ is the coefficient of risk aversion, for which we use a value of three. $\hat{r}_{t:t+k}$ is the k-month continuously compounded predicted excess market return based on the predictive regression (7)

$$\hat{r}_{t:t+k} = \hat{\alpha}_t + \hat{\beta}_t z_t,$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are estimated using data up to time t. The forecast of the market excess return's variance is denoted by $\hat{\sigma}^2_{t:t+k}$, which is estimated using the sample variance of the excess returns over a rolling window of the past five years multiplied by k. The 13 predictive variables (z_t) that we use are: the proxy for sectoral shifts (CSV), the log dividend price ratio (logDP), the de-meaned risk-free rate (RF), the log price earnings ratio (logPE), the log net payout yield (logNPY), the default spread (DEF), term spread (TERM), inflation rate (INFL), and the consumption-wealth ratio (CAY), payroll growth (PYRL), net hiring rate (NetHR), net job creation in manufacturing (NetJC), and short interest index (SII). Panel A shows the annualized sample mean and standard deviation of the excess returns for portfolios where CSV is used as the predictive variable for different investment horizons, and compares them to the benchmark portfolio where the market excess return is predicted using the historical mean excess return. Panel B illustrates the difference between the realized certainty equivalence of the trading strategy for each predictive variable amd that of the benchmark. The certainty equivalent (CE) for each strategy is defined as

$$CE = \bar{r}_p - \frac{\gamma}{2}\hat{\sigma}^2_p,$$

where $\bar{r}_p$ and $\hat{\sigma}^2_p$ are the annualized sample mean and variance respectively of the excess portfolio return associated with each trading strategy, calculated over all out-of-sample returns. The t-ratios associated with the CE differences are derived in the Internet Appendix. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively, for a one-sided test.

Table VII: **Trading Strategies based on CSV and Alternative Predictors** – ***continued***

Panel A: Portfolios Constructed Using CSV vs. Historical Mean Benchmark

	Mean	Std. Dev.	Certainty Equivalent
CSV (k=1)	9.21%	17.69%	4.52%
CSV (k=3)	12.06%	19.98%	6.07%
CSV (k=12)	11.21%	18.97%	5.81%
CSV (k=24)	9.60%	17.96%	4.76%
CSV (k=36)	7.68%	15.85%	3.92%
Benchmark	5.44%	16.23%	1.49%

Panel B: Certainty Equivalent Differences for Different Predictive Variables

k		CSV	logDP	RF	logPE	logNPY	DEF	TERM	INFL	CAY	PYRL	NetHR	NetJC	SII
1	ΔCE	3.03*	−4.06	−4.20	−2.25	−5.74	−3.02	−1.90	−6.41	0.36	−1.84	−1.35	−0.08	0.65
	t-ratio	(1.39)	(−1.36)	(−1.25)	(−1.41)	(−2.2)	(−1.62)	(−0.46)	(−1.1)	(0.11)	(−1.56)	(−0.86)	(−0.04)	(0.14)
3	ΔCE	4.58**	−4.96	−0.44	−2.85	−6.15	−3.31	−1.54	−3.56	0.46	−2.28	−1.58	−0.05	0.46
	t-ratio	(1.66)	(−1.48)	(−0.35)	(−1.54)	(−2.41)	(−1.81)	(−0.43)	(−0.88)	(0.12)	(−1.36)	(−1.27)	(−0.02)	(0.09)
12	ΔCE	4.32***	−7.28	−0.10	−3.05	−6.99	−1.51	1.43	0.10	1.12	−2.27	−5.30	1.08	−0.71
	t-ratio	(2.00)	(−1.81)	(−0.08)	(−1.31)	(−1.64)	(−1.27)	(0.67)	(0.05)	(0.37)	(−1.04)	(−1.55)	(0.68)	(−0.15)
24	ΔCE	3.27***	−6.65	0.40	−1.51	−2.58	−0.17	2.23***	0.62	0.99	−0.08	−1.54	−0.05	−0.93
	t-ratio	(1.98)	(−1.74)	(0.44)	(−0.70)	(−0.71)	(−0.18)	(2.35)	(0.50)	(0.29)	(−0.07)	(−0.65)	(−0.06)	(−0.44)
36	ΔCE	2.43***	−4.08	0.68	−0.45	−0.34	−0.22	2.45***	0.86	0.86	0.63	−0.31	−0.37	−0.89
	t-ratio	(2.23)	(−1.20)	(0.72)	(−0.24)	(−0.12)	(−0.19)	(2.31)	(0.76)	(0.27)	(0.61)	(−0.13)	(−0.41)	(−0.44)

Table VIII: **Model Parameters**

The table reports the values of the calibrated parameters used in our benchmark model at monthly frequency.

Description	Symbol	Value
Technology		
Output elasticity of labor	α	0.70
Total separation rate	δ	0.03
Adjustment cost coefficient	κ	200
Sensitivity of the wage rate to aggregate productivity	τ	1
Preferences and shocks		
Time discount factor	β	0.997
Constant component of the price of risk	γ_0	2.3
Coefficient of the counter-cyclical component of the price of risk	γ_1	-2.76
Persistence coefficient of aggregate productivity shock	ρ_x	0.95
Conditional volatility of aggregate productivity shock	σ_x	0.0137
Persistence coefficient of sectoral reallocation shock	ρ_s	0.96
Conditional volatility of sectoral reallocation shock	σ_s	0.1
Persistence coefficient of industry level productivity shock	$\rho_{\tilde{z}}$	0.965
Conditional volatility of industry level productivity shock	$\sigma_{\tilde{z}}$	0.262

Table IX: **Aggregate Moments**

The table reports the target aggregate moments for the calibrated model. We present the median along with 40 percentile and 60 percentile of the moments from our cross-simulation distribution based on 500 simulations, and compare it with moments derived from historical data. Moments associated with returns are reported in annual frequency. The sample period for the moments associated with historical data is from January 1952 to December 2013.

		Simulation		
Moments	Data	40%	Median	60%
$\mathbb{E}[R_m - R_f](\%)$	7.01	3.70	4.13	5.34
$\sigma[R_m - R_f](\%)$	15.02	31.23	32.58	33.60
$\mathbb{E}[R_f](\%)$	3.45	3.19	3.41	3.84
$\sigma[R_f](\%)$	0.88	1.63	1.67	1.70
$\mathbb{E}[CSV]$	0.155	0.401	0.415	0.427
$\sigma[CSV]$	0.044	0.209	0.221	0.239
$\rho[CSV]$	0.909	0.881	0.887	0.900

Table X: **Simulation Results: Market Return Predictability**

The table reports results of the following predictive regression based on simulated data:

$$r_{t:t+k} = \alpha + \beta CSV_t + \varepsilon_{t:t+k},$$

where $r_{t:t+k}$ is the continuously compounded k-month excess return on the market from month t to month $t+k$, and CSV_t is the time t value of the CSV, both obtained through simulation. The table reports the cross-simulation median of the regression coefficient estimate ($\hat{\beta}$) and Newey-West (1987) adjusted (based on $k-1$ lags) t-ratios, as well as the in-sample R^2s for 100 simulations. The five columns show results for $k = 1, 3, 12, 24$ and 36 months. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Excess market return predictability					
	$k=1$	$k=3$	$k=12$	$k=24$	$k=36$
$\hat{\beta}$	-0.028	-0.079	-0.272	-0.39	-0.498
t-ratio$_{NW}$	(-1.47)	$(-1.82)^{*}$	$(-2.37)^{**}$	$(-2.62)^{***}$	$(-2.58)^{***}$
R^2_{IS}	0.46%	1.18%	4.14%	6.03%	7.06%

Table XI: **Simulation Results: Conditional Covariance between Market Return and Pricing Kernel**

The table reports the covariance between 12-month market excess return and the pricing kernel. Each simulation episode is divided into 5 sub-periods based on the value of the cross-sectional dispersion in industry productivity (S_t). We calculate the continuously compounded excess return on the market cap-weighted market return (Panel A) and equally-weighted market return (Panel B) from month t to month $t+12$ and find the covariance between the the excess market return and pricing kernel $M_{t:t+12}$ over each sub-period, scaled by the 12-month volatility of the pricing kernel.

Panel A: Value Weighted Market Return						
	Low S_t	2	3	4	High S_t	High–Low
$k = 1$	-0.001	0.000	-0.001	0.000	0.001	0.002
$k = 3$	-0.037	-0.036	-0.038	-0.036	-0.034	0.003
$k = 12$	-0.096	-0.099	-0.091	-0.098	-0.074	0.023
$k = 24$	-0.128	-0.127	-0.123	-0.130	-0.093	0.035
$k = 36$	-0.145	-0.158	-0.152	-0.132	-0.107	0.038
Panel B: Equally Weighted Market Return						
	Low S_t	2	3	4	High S_t	High–Low
$k = 1$	0.000	0.000	-0.001	0.000	0.001	0.001
$k = 3$	-0.037	-0.037	-0.037	-0.039	-0.035	0.002
$k = 12$	-0.095	-0.095	-0.095	-0.105	-0.088	0.007
$k = 24$	-0.135	-0.137	-0.135	-0.149	-0.128	0.007
$k = 36$	-0.162	-0.172	-0.175	-0.158	-0.144	0.017

Table XII: **Simulation Results: Industry Productivity and Expected Returns**

The table reports the covariance between 12-month industry excess returns and the pricing kernel, as well as the industry expected returns conditional on the relative level of the industry's idiosyncratic productivity and the dispersion in the productivity of industries. Each simulation episode is divided into 5 sub-periods based on the value of the cross-sectional dispersion in industry productivity (S_t). At the beginning of each month, we rank industries into quintile portfolios based on the level of their standardized idiosyncratic productivity ($\tilde{z}_{i,t}$) and calculate the continuously compounded excess return on each portfolio from month t to month $t+12$. Panel A reports cross-episode median of the covariance between the 12-month return of each portfolio and the pricing kernel $M_{t:t+12}$ from t to $t+12$ over each subperiod, scaled by the 12-month volatility of the pricing kernel. Panel B reports the median of the time-series average of excess return for each portfolio from month t to month $t+12$ within each subperiod across simulation episodes.

Panel A: Conditional Covariance between Industry Returns and Pricing Kernel

	Low-Productivity	2	3	4	High-Productivity	High–Low
Low S_t	−0.094	−0.095	−0.096	−0.101	−0.094	0.001
2	−0.099	−0.097	−0.096	−0.098	−0.089	0.010
3	−0.102	−0.098	−0.097	−0.099	−0.084	0.018
4	−0.100	−0.102	−0.104	−0.103	−0.084	0.016
High S_t	−0.094	−0.088	−0.092	−0.085	−0.072	0.022
High–Low	0.001	0.007	0.004	0.016	0.022	0.021

Panel B: Conditional Expected Industry Return

	Low-Productivity	2	3	4	High-Productivity	High–Low
Low S_t	0.088	0.082	0.077	0.073	0.031	−0.057
2	0.081	0.077	0.069	0.064	0.028	−0.054
3	0.087	0.078	0.075	0.075	0.020	−0.067
4	0.076	0.062	0.066	0.070	−0.010	−0.086
High S_t	0.065	0.044	0.032	0.017	−0.100	−0.165
High–Low	−0.023	−0.037	−0.045	−0.057	−0.131	−0.108

Table XIII: **Equally-Weighted Market Return Predictability**

The table reports results of the following predictive regression:

$$r_{t:t+k} = \alpha + \beta CSV_t + \varepsilon_{t:t+k},$$

where $r_{t:t+k}$ is the continuously compounded k-month excess return on the equally-weighted market portfolio from month t to month $t+k$, and CSV_t is the time t value of the CSV, both obtained through simulation (Panel A) and actual data between January 1952 and December 2019 (Panel B). The table reports the the regression coefficient estimate ($\hat{\beta}$), the corresponding Hodrick (1992) and Newey-West (1987) adjusted (based on $k-1$ lags) t-ratios, as well as the in-sample R^2s for 100 simulations. The five columns show results for $k = 1, 3, 12, 24$ and 36 months. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Return Predictability based on Simulated Data					
	$k=1$	$k=3$	$k=12$	$k=24$	$k=36$
$\hat{\beta}$	-0.009	-0.027	-0.102	-0.144	-0.208
t-ratio$_{NW}$	(-0.87)	(-1.14)	(-1.13)	(-1.22)	(-1.19)
R^2_{IS}	0.12%	0.38%	1.28%	1.94%	2.63%
Panel B: Return Predictability based on Actual Data					
	$k=1$	$k=3$	$k=12$	$k=24$	$k=36$
$\hat{\beta}$	-0.018	-0.198	-0.634	-0.838	-0.449
t-ratio$_{Hodr}$	(-0.34)	(-1.25)	(-1.11)	(-0.89)	(-0.37)
t-ratio$_{NW}$	(-0.34)	(-1.50)	$(-1.78)^{*}$	(-1.52)	(-0.64)
R^2_{IS}	0.02%	0.63%	1.62%	1.65%	0.37%
R^2_{OOS}	-0.44%	-0.31%	-0.57%	-5.30%	-15.51%

Table XIV: **Predicting Industry Equity Returns Using CSV**

The table reports results of predictive regressions of CSV for future industry returns. Each month, we sort returns on industry portfolios into quintiles, based on their past 12-month compounded idiosyncratic returns. Next, we use CSV to predict the time series of the continuously compounded k-month excess returns on each of the industry quintile portfolios (equally weighted) using a similar predictive regression as (7). Panel A shows the results when time series are generated using simulations, where the reported values are the cross-simulation median of the regression coefficient estimate ($\hat{\beta}$) and Newey-West (1987) adjusted (based on $k-1$ lags) t-ratios, as well as the in-sample R^2s for 500 simulations. Panel B reports the results based on actual data from January 1952 to December 2019. The panel reports the in-sample regression coefficient estimates ($\hat{\beta}$), the corresponding t-ratios of Hodrick (1992) and Newey-West (1987) with $k-1$ lags, as well as the in-sample and out-of-sample R^2s. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Industry Excess Return Predictability based on Simulated Data

		Loser	2	3	4	Winner
$k=1$	$\hat{b}_1$	-0.009	-0.007	-0.005	-0.008	-0.03
	t-ratio$_{NW}$	(-0.7)	(-0.71)	(-0.5)	(-0.8)	(-1.44)
	R^2_{IS}	0.17%	0.1%	0.06%	0.12%	0.33%
$k=3$	$\hat{b}_1$	-0.03	-0.02	-0.019	-0.022	-0.074
	t-ratio$_{NW}$	(-1.09)	(-0.89)	(-0.96)	(-0.95)	(-1.64)
	R^2_{IS}	0.37%	0.26%	0.21%	0.26%	0.79%
$k=12$	$\hat{b}_1$	-0.097	-0.074	-0.065	-0.087	-0.251
	t-ratio$_{NW}$	(-1.23)	(-1.09)	(-1.02)	(-1.27)	$(-2.08)^{**}$
	R^2_{IS}	1.15%	0.91%	0.64%	0.86%	2.46%
$k=24$	$\hat{b}_1$	-0.171	-0.128	-0.1	-0.134	-0.387
	t-ratio$_{NW}$	(-1.47)	(-1.28)	(-1.08)	(-1.29)	$(-2.18)^{**}$
	R^2_{IS}	2.15%	1.49%	1.12%	1.27%	3.79%
$k=36$	$\hat{b}_1$	-0.226	-0.162	-0.133	-0.175	-0.455
	t-ratio$_{NW}$	(-1.44)	(-1.08)	(-1.08)	(-1.23)	$(-1.98)^{**}$
	R^2_{IS}	2.45%	1.64%	1.41%	1.6%	4.53%

Table XIV: **Predicting Industry Equity Returns Using CSV –** ***continued***

Panel B: Industry Excess Return Predictability based on Actual Data						
		Loser	2	3	4	Winner
$k = 1$	$\hat{\beta}$	-0.048	-0.015	-0.062	-0.061	-0.091
	t-ratio$_{Hodr}$	(-1.01)	(-0.41)	$(-1.71)^{*}$	(-1.60)	$(-2.02)^{**}$
	t-ratio$_{NW}$	(-1.01)	(-0.40)	$(-1.70)^{*}$	(-1.61)	$(-2.06)^{**}$
	R^2_{IS}	0.14%	0.02%	0.35%	0.33%	0.60%
	R^2_{OOS}	-0.24%	-0.31%	0.12%	0.09%	0.34%
$k = 3$	$\hat{\beta}$	-0.236	-0.185	-0.233	-0.308	-0.350
	t-ratio$_{Hodr}$	(-1.64)	(-1.54)	$(-2.08)^{**}$	$(-2.62)^{***}$	$(-2.47)^{**}$
	t-ratio$_{NW}$	$(-2.01)^{**}$	$(-1.84)^{*}$	$(-2.64)^{***}$	$(-3.04)^{***}$	$(-2.50)^{**}$
	R^2_{IS}	1.03%	0.80%	1.48%	2.48%	2.59%
	R^2_{OOS}	0.28%	-0.13%	0.87%	2.30%	1.91%
$k = 12$	$\hat{\beta}$	-0.77	-0.615	-0.698	-0.873	-1.197
	t-ratio$_{Hodr}$	(-1.42)	(-1.45)	$(-1.74)^{*}$	$(-2.14)^{**}$	$(-2.52)^{**}$
	t-ratio$_{NW}$	$(-1.90)^{*}$	$(-1.97)^{**}$	$(-2.37)^{**}$	$(-3.12)^{***}$	$(-2.89)^{***}$
	R^2_{IS}	2.91%	2.45%	3.34%	5.51%	8.11%
	R^2_{OOS}	3.17%	1.26%	2.30%	6.59%	10.50%
$k = 24$	$\hat{\beta}$	-0.989	-0.824	-1.003	-1.296	-2.137
	t-ratio$_{Hodr}$	(-1.14)	(-1.20)	(-1.46)	$(-1.97)^{**}$	$(-2.90)^{***}$
	t-ratio$_{NW}$	$(-2.26)^{**}$	$(-2.49)^{**}$	$(-2.66)^{***}$	$(-3.23)^{***}$	$(-4.20)^{***}$
	R^2_{IS}	3.19%	2.84%	4.13%	6.90%	13.66%
	R^2_{OOS}	14.76%	4.99%	5.07%	9.20%	20.94%
$k = 36$	$\hat{\beta}$	-0.796	-0.661	-0.877	-1.146	-1.999
	t-ratio$_{Hodr}$	(-0.72)	(-0.74)	(-0.96)	(-1.32)	$(-2.10)^{**}$
	t-ratio$_{NW}$	(-1.50)	(-1.60)	$(-1.94)^{*}$	$(-2.32)^{**}$	$(-3.07)^{***}$
	R^2_{IS}	1.78%	1.48%	2.47%	4.08%	8.93%
	R^2_{OOS}	28.90%	5.40%	2.83%	2.18%	16.85%

Table XV: **Predicting Stock Market Returns Using Labor Skill-Based CSV**

The table reports results of a predictive regression where the dependent variable is the continuously compounded k-month excess return on the market from month t to month $t+k$. We use as the independent variables the high skill CSV (CSV_{HS}) and low skill CSV (CSV_{LS}) at time t, constructed respectively using industries that belong to the upper tercile and lower tercile in terms of industry skill. Panel A reports the results when industry skill is defined as the percentage of workers in the industry that are high skill workers. Panel B shows the results when industry skill is defined as the percentage of total wages in the industry that is associated with high skill workers. Industries are defined at the two-digit SIC level prior to 2002, and at three-digit NAICS level afterwards. The sample is from 1991 to 2019. The table reports the regression coefficient estimate, the corresponding t-ratios of Hodrick (1992) and Newey-West (1987) with $k-1$ lags, as well as the in-sample R^2s. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Industry Skill Level Weighted by Employment

	$k=1$			$k=3$			$k=12$			$k=24$			$k=36$		
CSV_{HS}	−0.111		−0.112	−0.316		−0.287	−1.408		−1.442	−1.990		−2.257	−2.765		−2.948
t-ratio$_{Hodr}$	(−1.96)**		(−1.66)*	(−1.97)**		(−1.49)	(−2.37)**		(−2.01)**	(−1.81)*		(−1.96)**	(−1.8)*		(−1.96)**
t-ratio$_{NW}$	(−2.04)**		(−1.71)*	(−2.7)****		(−2.33)**	(−3.66)***		(−3.44)***	(−2.10)**		(−2.08)**	(−2.37)**		(−2.44)**
CSV_{LS}		−0.082	0.002		−0.271	−0.055		−1.029	0.066		−1.245	0.499		−1.902	0.344
t-ratio$_{Hodr}$		(−1.37)	(0.03)		(−1.67)*	(−0.29)		(−1.77)*	(0.10)		(−1.23)	(0.60)		(−1.44)	(0.48)
t-ratio$_{NW}$		(−1.36)	(0.03)		(−1.88)*	(−0.37)		(−1.96)**	(0.12)		(−1.64)	(0.80)		(−1.85)*	(0.45)
R^2_{IS}	1.64%	0.61%	1.64%	4.21%	2.12%	4.26%	17.99%	6.65%	18.01%	16.50%	4.46%	16.92%	21.39%	7.06%	21.52%

Panel B: Industry Skill Level Weighted by Wages

	$k=1$			$k=3$			$k=12$			$k=24$			$k=36$		
CSV_{HS}	−0.079		−0.054	−0.247		−0.171	−1.160		−0.985	−2.033		−2.157	−2.671		−2.572
t-ratio$_{Hodr}$	(−1.41)		(−0.87)	(−1.58)		(−0.98)	(−2.05)**		(−1.52)	(−1.96)**		(−2.11)**	(−1.88)*		(−1.99)**
t-ratio$_{NW}$	(−1.45)		(−0.90)	(−2.16)**		(−1.44)	(−3.20)***		(−2.23)**	(−2.39)**		(−2.58)**	(−2.60)***		(−2.76)***
CSV_{LS}		−0.098	−0.069		−0.304	−0.212		−1.010	−0.472		−0.856	0.333		−1.657	−0.271
t-ratio$_{Hodr}$		(−1.66)*	(−1.06)		(−1.84)*	(−1.16)		(−1.58)	(−0.64)		(−0.86)	(0.37)		(−1.31)	(−0.32)
t-ratio$_{NW}$		(−1.66)*	(−1.07)		(−2.04)**	(−1.40)		(−1.91)*	(−0.69)		(−1.23)	(0.51)		(−1.57)	(−0.38)
R^2_{IS}	0.87%	0.91%	1.24%	2.70%	2.73%	3.78%	12.81%	6.58%	13.95%	18.14%	2.17%	18.40%	21.20%	5.53%	21.32%

Table XVI: **Predicting Stock Market Returns Using CSV Based on Industries With High– and Low– Asset Redeployability**

The table reports results of a predictive regression where the dependent variable is the continuously compounded k-month excess return on the market from month t to month $t+k$. We use as the independent variables the high-redeployability CSV (CSV_{HR}) and low-redeployability CSV (CSV_{LR}) at time t, constructed respectively using industries that belong to the highest tercile and lowest tercile in terms of industry-level asset redeployability index, defined by Kim and Kung (2017). Panel A reports the results when asset-level redeployability score is defined based on the market capitalization of the industries that use the asset. Panel B shows the results when asset-level redeployability score is defined based on the number of industries that utilize the asset. Industries are defined based on BEA industry classification, where we consider industries that consist of at least 5 firms. The sample period is from 1985 to 2019. The table reports the regression coefficient estimate, the corresponding t-ratios of Hodrick (1992) and Newey-West (1987) with $k-1$ lags, as well as the in-sample R^2s. ***, **, and * indicate significance at the 1%, 5% and 10% levels.

Table XVI: **Predicting Stock Market Returns Using CSV Based on Industries With High– and Low– Asset Redeployability –** ***continued***

		Panel A: Value-Weighted Asset Redeployability Score			Panel B: Equally-Weighted Asset Redeployability Score		
$k=1$	CSV_{HR}	-0.107		-0.061	-0.131		-0.089
	$t\text{-ratio}_{Hodr}$	$(-2.40)^{**}$		(-1.20)	$(-2.74)^{***}$		(-1.58)
	$t\text{-ratio}_{NW}$	$(-2.53)^{**}$		(-1.25)	$(-2.96)^{***}$		$(-1.67)^{*}$
	CSV_{LR}		-0.143	-0.100		-0.146	-0.086
	$t\text{-ratio}_{Hodr}$		$(-2.87)^{***}$	$(-1.78)^{*}$		$(-2.90)^{***}$	(-1.48)
	$t\text{-ratio}_{NW}$		$(-3.13)^{***}$	$(-1.91)^{*}$		$(-3.18)^{***}$	(-1.60)
	R^2_{IS}	2.48%	2.89%	3.45%	3.23%	2.94%	3.91%
$k=3$	CSV_{HR}	-0.374		-0.236	-0.437		-0.304
	$t\text{-ratio}_{Hodr}$	$(-2.65)^{***}$		(-1.61)	$(-2.91)^{***}$		$(-1.89)^{*}$
	$t\text{-ratio}_{NW}$	$(-4.44)^{***}$		$(-2.66)^{***}$	$(-4.79)^{***}$		$(-2.90)^{***}$
	CSV_{LR}		-0.466	-0.302		-0.472	-0.270
	$t\text{-ratio}_{Hodr}$		$(-2.73)^{***}$	$(-1.71)^{*}$		$(-2.75)^{***}$	(-1.48)
	$t\text{-ratio}_{NW}$		$(-3.96)^{***}$	$(-2.24)^{**}$		$(-4.01)^{***}$	$(-1.90)^{*}$
	R^2_{IS}	9.18%	9.35%	11.86%	10.80%	9.34%	12.83%
$k=12$	CSV_{HR}	-1.525		-1.270	-1.750		-1.552
	$t\text{-ratio}_{Hodr}$	$(-2.70)^{***}$		$(-2.43)^{**}$	$(-2.84)^{***}$		$(-2.64)^{***}$
	$t\text{-ratio}_{NW}$	$(-4.59)^{***}$		$(-3.03)^{***}$	$(-5.18)^{***}$		$(-3.40)^{***}$
	CSV_{LR}		-1.434	-0.568		-1.424	-0.406
	$t\text{-ratio}_{Hodr}$		$(-2.43)^{**}$	(-1.22)		$(-2.44)^{**}$	(-0.88)
	$t\text{-ratio}_{NW}$		$(-4.22)^{***}$	(-1.55)		$(-4.05)^{***}$	(-1.02)
	R^2_{IS}	33.18%	19.34%	35.29%	37.50%	18.48%	38.52%
$k=24$	CSV_{HR}	-2.122		-2.079	-2.197		-2.212
	$t\text{-ratio}_{Hodr}$	$(-2.51)^{**}$		$(-2.54)^{**}$	$(-2.49)^{**}$		$(-2.57)^{**}$
	$t\text{-ratio}_{NW}$	$(-4.17)^{***}$		$(-4.76)^{***}$	$(-3.45)^{***}$		$(-4.29)^{***}$
	CSV_{LR}		-1.568	-0.092		-1.479	0.029
	$t\text{-ratio}_{Hodr}$		$(-1.82)^{*}$	(-0.13)		$(-1.75)^{*}$	(0.04)
	$t\text{-ratio}_{NW}$		(-1.64)	(-0.11)		(-1.50)	(0.03)
	R^2_{IS}	30.40%	10.89%	30.42%	28.01%	9.36%	28.01%
$k=36$	CSV_{HR}	-2.122		-1.714	-2.383		-2.133
	$t\text{-ratio}_{Hodr}$	$(-1.99)^{**}$		$(-1.71)^{*}$	$(-2.13)^{**}$		$(-2.00)^{**}$
	$t\text{-ratio}_{NW}$	$(-2.63)^{***}$		$(-2.42)^{**}$	$(-2.77)^{***}$		$(-3.12)^{***}$
	CSV_{LR}		-2.040	-0.826		-1.934	-0.467
	$t\text{-ratio}_{Hodr}$		$(-1.97)^{**}$	(-1.08)		$(-1.90)^{*}$	(-0.62)
	$t\text{-ratio}_{NW}$		$(-1.99)^{**}$	(-0.97)		$(-1.82)^{*}$	(-0.51)
	R^2_{IS}	19.47%	12.55%	20.81%	21.19%	10.85%	21.59%

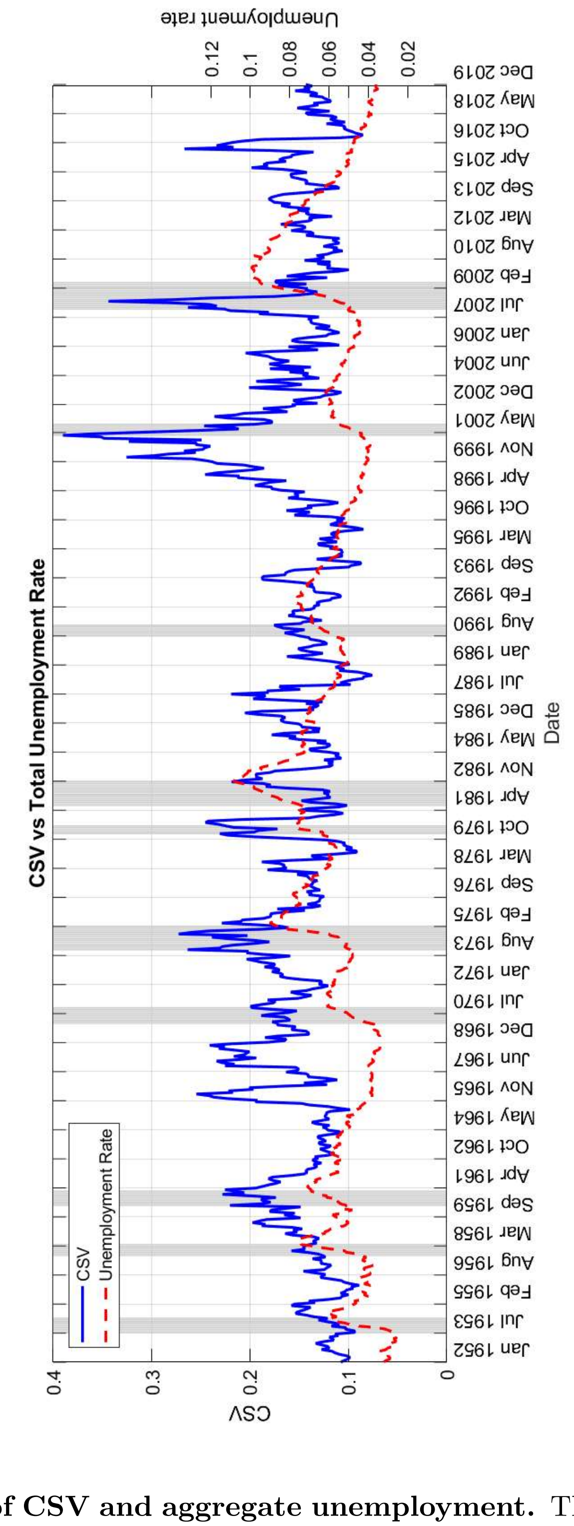

Figure 1. Time series of CSV and aggregate unemployment. The solid line shows the time series of our monthly CSV measure, which is computed based on the past 12 months of industry-specific returns (i.e., from month $t-11$ to t). The dashed line shows the aggregate unemployment rates (in levels) at time t. The shaded areas correspond to NBER recession dates.

Sectoral Labor Reallocation and Return Predictability

Internet Appendix

Esther Eiling, Raymond Kan and Ali Sharifkhani

This document presents the derivation of a statistical test for the equality of certainty equivalents of two different trading strategies as well as the results of several robustness tests for the paper. First, we present our derivation of the certainty equivalent statistical test. For our robustness tests, we begin by showing the results when we use our proxy for sectoral reallocation shocks (CSV) to predict individual industry rather than market equity returns. Then, we condition CSV on a measure of analyst coverage to examine slow information diffusion as an alternative explanation of its predictive power. Next, we use different horizons of past industry returns (3 months and 24 months) and different weighting schemes (employment-based weights and market capitalization-based weights) to construct CSV. Further, we use total rather than idiosyncratic industry returns in constructing our CSV measure, as well as use CSVs based on individual stocks or based on 100 size and book-to-market ranked portfolios rather than industry portfolios. Finally, we perform the analysis for three different subsample periods.

A. Test of Certainty Equivalent Differences

Suppose we have returns on two portfolios, $r_{1,t}$ and $r_{2,t}$ for $t = 1, \ldots, T$. Let $\mu_i = E[r_{i,t}]$ and $\sigma_i^2 = \mathrm{Var}[r_{i,t}]$. The certainty equivalents of the two portfolios are given by

$$U_1 = \mu_1 - \frac{\gamma}{2}\sigma_1^2, \qquad U_2 = \mu_2 - \frac{\gamma}{2}\sigma_2^2. \tag{IA.1}$$

The sample estimates of U_1 and U_2 are given by

$$\hat{U}_1 = \hat{\mu}_1 - \frac{\gamma}{2}\hat{\sigma}_1^2, \qquad \hat{U}_2 = \hat{\mu}_2 - \frac{\gamma}{2}\hat{\sigma}_2^2, \tag{IA.2}$$

where $\hat{\mu}_i$ and $\hat{\sigma}_i^2$ are the sample mean and variance of portfolio i, for $i = 1, 2$. Under joint stationarity and ergodicity assumption on $\{r_{1t}, r_{2t}\}$, the joint asymptotic distribution of $(\hat{\mu}_1, \hat{\mu}_2, \hat{\sigma}_1^2, \hat{\sigma}_2^2)$ is given by

$$\sqrt{T}\begin{bmatrix} \hat{\mu}_1 - \mu_1 \\ \hat{\mu}_2 - \mu_2 \\ \hat{\sigma}_1^2 - \sigma_1^2 \\ \hat{\sigma}_2^2 - \sigma_2^2 \end{bmatrix} \stackrel{A}{\sim} N\left(\mathbf{0}, \sum_{j=-\infty}^{\infty} E[h_t h_{t+j}']\right), \tag{IA.3}$$

where

$$h_t = \begin{bmatrix} r_{1,t} - \mu_1 \\ r_{2,t} - \mu_2 \\ (r_{1,t} - \mu_1)^2 - \sigma_1^2 \\ (r_{2,t} - \mu_2)^2 - \sigma_2^2 \end{bmatrix}. \tag{IA.4}$$

Using the delta method, we have

$$\sqrt{T}(\hat{U}_1 - \hat{U}_2 - (U_1 - U_2)) \stackrel{A}{\sim} N\left(0, \sum_{j=-\infty}^{\infty} E[g_t g_{t+j}]\right), \tag{IA.5}$$

where

$$g_t = r_{1,t} - \frac{\gamma}{2}(r_{1,t} - \mu_1)^2 - r_{2,t} + \frac{\gamma}{2}(r_{2,t} - \mu_2)^2 - (U_1 - U_2). \tag{IA.6}$$

For constructing the estimated standard error of $\hat{U}_1 - \hat{U}_2$, we replace g_t with its sample counterpart

$$\hat{g}_t = r_{1,t} - \frac{\gamma}{2}(r_{1,t} - \hat{\mu}_1)^2 - r_{2,t} + \frac{\gamma}{2}(r_{2,t} - \hat{\mu}_2)^2 - (\hat{U}_1 - \hat{U}_2), \tag{IA.7}$$

and use zero lags as returns are almost serially uncorrelated.

Table AI. Predicting Individual Industry Returns Using CSV

This table reports results of predictive regressions for individual industry returns of 49 industries. We regress our proxy for sectoral shifts (CSV) on log industry excess returns over the next 12 months:

$$r_{i,t:t+12} = \alpha_i + \beta_i CSV_t + \varepsilon_{i,t:t+12},$$

where $r_{i,t:t+12}$ is the continuously compounded 12-month excess return for industry i from month t to month $t+12$. The table reports the regression coefficient estimate ($\hat{\beta}$), the corresponding t-ratios of Hodrick (1992) and Newey-West (1987) with $k-1$ lags, as well as the in-sample and out-of-sample R^2s. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Industry	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
Agriculture	−1.22	(−2.46)**	(−2.68)***	6.65%	1.51%
Food Products	−0.46	(−1.28)	(−1.45)	1.69%	3.23%
Candy and Soda	−0.77	(−1.21)	(−1.78)*	2.63%	1.63%
Beer and Liquor	−1.07	(−2.38)**	(−3.36)***	7.45%	8.74%
Tobacco Products	−0.01	(−0.02)	(−0.02)	0.00%	1.93%
Recreation	−1.15	(−1.86)*	(−2.26)**	3.1%	−9.18%
Entertainment	−0.81	(−1.11)	(−1.36)	1.61%	1.73%
Printing and Publishing	−1.16	(−2.35)**	(−2.50)**	4.67%	−3.62%
Consumer Goods	−0.85	(−2.12)**	(−2.44)**	4.75%	−4.83%
Apparel	−0.59	(−1.01)	(−1.39)	1.18%	−0.38%
Healthcare	−0.35	(−0.47)	(−0.50)	0.24%	−11.05%
Medical Equipment	−0.81	(−1.84)*	(−2.60)***	3.5%	−4.04%
Pharmaceutical Products	−1.22	(−2.82)***	(−4.70)***	8.95%	7.32%
Chemicals	−0.89	(−1.82)*	(−2.53)**	4.35%	2.23%
Rubber and Plastic Products	−0.84	(−1.57)	(−2.02)**	3.19%	−1.96%
Textiles	−0.38	(−0.55)	(−0.71)	0.4%	−2.92%
Construction Materials	−0.83	(−1.55)	(−2.08)**	3.33%	2.47%
Construction	−0.60	(−0.96)	(−1.24)	1.08%	−2.39%
Steel Works Etc	−1.11	(−1.43)	(−1.89)*	3.61%	−3.91%
Fabricated Products	−1.22	(−1.85)*	(−2.77)***	4.93%	4.31%
Machinery	−0.86	(−1.37)	(−2.04)**	3.26%	−1.71%

Table AI - continued

Industry	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
Electrical Equipment	−1.65	(−2.72)*	(−4.11)*	12.24%	10.02%
Automobiles and Trucks	−1.08	(−1.63)*	(−2.58)*	3.72%	−0.08%
Aircraft	−1.62	(−2.41)*	(−3.28)*	7.4%	1.88%
Shipbuilding, Railroad Equipment	−0.72	(−1.18)*	(−1.38)*	1.94%	−2.96%
Defense	−0.04	(−0.06)*	(−0.06)*	0.01%	−4.81%
Precious Metals	0.25	(0.28)*	(0.36)*	0.12%	−14.86%
Non-Metallic and Industrial Metal Mining	−0.59	(−0.95)*	(−1.29)*	1.03%	−3.17%
Coal	0.90	(0.84)*	(0.99)*	1.11%	−4.75%
Petroleum and Natural Gas	−0.89	(−1.91)*	(−2.61)*	4.54%	2.86%
Utilities	−0.76	(−1.95)*	(−2.26)*	5.65%	3.37%
Communication	−1.51	(−3.17)*	(−3.55)*	13.78%	11.33%
Personal Services	−0.64	(−1.34)*	(−1.36)*	1.19%	−8.52%
Business Services	−1.22	(−2.33)*	(−3.83)*	7.54%	7.84%
Computers	−1.81	(−1.99)*	(−2.72)*	8.49%	−2.25%
Computer Software	−2.07	(−2.09)*	(−3.57)*	5.75%	6.21%
Electronic Equipment	−1.89	(−2.15)*	(−3.2)*	9.44%	2.00%
Measuring and Control Equipment	−1.29	(−1.76)*	(−2.74)*	5.91%	1.82%
Business Supplies	−0.21	(−0.45)*	(−0.58)*	0.22%	−0.08%
Shipping Containers	−0.68	(−1.2)*	(−1.33)*	2.63%	−2.12%
Transportation	−0.82	(−1.7)*	(−2.45)*	3.22%	2.72%
Wholesale	−0.85	(−1.81)*	(−2.47)*	3.53%	4.05%
Retail	−0.74	(−1.57)*	(−2.52)*	3.08%	3.24%
Restaurants, Hotels, Motels	−0.79	(−1.56)*	(−2.03)*	2.1%	−0.66%
Banking	−0.72	(−1.39)*	(−1.72)*	2.28%	0.09%
Insurance	−0.76	(−1.47)*	(−1.8)*	3.00%	1.79%
Real Estate	−0.70	(−1.00)*	(−1.21)*	0.98%	−4.73%
Trading	−0.90	(−1.37)*	(−2.23)*	3.16%	2.87%
Other	−1.64	(−2.84)*	(−3.76)*	8.04%	8.51%

Table AII. The Role of Informed Investors

This table reports the effect of analyst coverage on the predictive power of CSV. At each month, we construct a measure of analyst coverage for each industry based on the average number of analyst announcement per firm over the past 6 months in the corresponding industry (Panel A) or the percentage of firms in the industry with at least one analyst announcement over the past 6 months (Panel B). We next construct $coverage_t$ at each month t by calculating the equally weighted average of the analyst coverage of the top and bottom 20 percentile of industries ranked in terms of past 12 months idiosyncratic return. We then run the following predictive regressions:

$$y_{t:t+k} = \alpha + \beta_1 CSV_t + \beta_2 coverage_t + \beta_3 CSV_t \times coverage_t + \varepsilon_{t:t+k},$$

where $y_{t:t+k}$ is the continuously compounded k-month excess return on the market from month t to month $t+k$. CSV_t is the equally weighted cross-sectional volatility of past 12-month compounded idiosyncratic returns on 49 industry portfolios. Each panel reports the regression coefficient estimate, the corresponding t-ratios of Hodrick (1992) and Newey-West (1987) with $k-1$ lags, and the in-sample R^2s. The sample period covers January 1984 to December 2019 ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Average Number of Analysts per Firm in the Industry						
		$k=1$	$k=3$	$k=12$	$k=24$	$k=36$
CSV	$\hat{\beta}_1$	−0.20	−0.60	−2.91	−6.07	−6.25
	t-ratio$_{Hodr}$	(−1.13)	(−1.25)	(−1.66)*	(−2.00)**	(−1.47)
	t-ratio$_{NW}$	(−1.15)	(−1.61)	(−2.76)***	(−4.55)***	(−2.67)***
coverage	$\hat{\beta}_2$	0.00	0.00	−0.04	−0.11	−0.09
	t-ratio$_{Hodr}$	(−0.43)	(−0.21)	(−0.71)	(−1.40)	(−0.73)
	t-ratio$_{NW}$	(−0.44)	(−0.26)	(−1.00)	(−2.64)***	(−1.09)
CSV×coverage	$\hat{\beta}_3$	0.02	0.03	0.29	0.87	0.81
	t-ratio$_{Hodr}$	(0.57)	(0.33)	(0.82)	(1.62)	(1.06)
	t-ratio$_{NW}$	(0.59)	(0.40)	(1.08)	(3.46)***	(1.69)*
	R^2_{IS}	1.56%	7.84%	26.45%	29.99%	30.51%

Panel B: Percentage of Firms in the Industry with at Least One Analyst						
		$k=1$	$k=3$	$k=12$	$k=24$	$k=36$
CSV	$\hat{\beta}_1$	−0.17	−0.51	−2.62	−6.56	−5.7
	t-ratio$_{Hodr}$	(−0.52)	(−0.50)	(−0.81)	(−1.30)	(−0.99)
	t-ratio$_{NW}$	(−0.51)	(−0.58)	(−1.07)	(−2.08)**	(−1.34)
coverage	$\hat{\beta}_2$	0.00	0.02	−0.13	−0.8	−0.37
	t-ratio$_{Hodr}$	(−0.01)	(0.09)*	(−0.18)	(−0.80)	(−0.30)
	t-ratio$_{NW}$	(−0.01)	(0.10)	(−0.24)	(−1.03)	(−0.33)
CSV×coverage	$\hat{\beta}_3$	0.09	0.08	1.52	6.60	4.43
	t-ratio$_{Hodr}$	(0.19)	(0.05)	(0.31)	(0.93)	(0.56)
	t-ratio$_{NW}$	(0.19)	(0.06)	(0.37)	(1.40)	(0.65)
	R^2_{IS}	1.54%	7.88%	25.73%	26.23%	26.79%

Table AIII. Predictive Regressions Using Alternative Horizons for CSV

This table reports results of predictive regressions on future unemployment growth (Panel A) and future excess market returns (Panel B) using CSV based on past three-month ($m = 3$) or past 24 month ($m = 24$) industry idiosyncratic returns, rather than using $m = 12$ as in our primary measure. We run the following predictive regressions:

$$y_{t:t+k} = \alpha + \beta CSV_t^m + \varepsilon_{t:t+k}.$$

For Panel A, $y_{t:t+k} = un_{t+k} - un_t$ where un_t is based on a log transformation of the unemployment rate: $un_t = \log(UN_t/(1 - UN_t))$. For Panel B, $y_{t:t+k} = r_{t:t+k}$, i.e., the continuously compounded k-month excess return on the market from month t to month $t + k$. CSV_t^m is the cross-sectional volatility of past m-month industry idiosyncratic returns. Panel A reports the regression coefficient estimate ($\hat{\beta}$), the corresponding Newey-West (1987) adjusted (based on $k - 1$ lags) t-ratios and the in-sample R^2s. In addition, Panel B reports Hodrick (1992) t-ratios and the out-of-sample R^2. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Predicting Aggregate Unemployment Growth

	$m = 3$			$m = 24$		
k	$\hat{\beta}$	t-ratio	R^2_{IS}	$\hat{\beta}$	t-ratio	R^2_{IS}
1	0.19	(2.84)***	1.19%	0.07	(3.21)***	1.69%
3	0.49	(2.59)***	1.99%	0.19	(2.68)***	2.71%
12	1.43	(1.57)	2.17%	0.53	(1.79)*	2.7%
24	1.96	(1.49)	2.04%	0.66	(1.22)	2.09%
36	2.09	(1.41)	1.73%	0.69	(1.11)	1.7%

Panel B: Predicting Excess Stock Market Returns

		$m = 3$			
k	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
1	−0.11	(−1.31)	(−1.30)	0.3%	−0.11%
3	−0.35	(−1.56)	(−1.82)*	0.92%	−0.28%
12	−1.82	(−2.35)**	(−2.71)***	5.68%	2.27%
24	−3.38	(−2.42)**	(−2.95)***	10.59%	8.37%
36	−4.03	(−2.16)**	(−2.77)***	11.24%	9.3%
		$m = 24$			
k	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
1	−0.06	(−2.26)**	(−2.25)**	0.8%	0.53%
3	−0.19	(−2.51)**	(−2.84)***	2.58%	1.61%
12	−0.66	(−2.43)**	(−2.46)**	6.94%	4.93%
24	−1.15	(−2.48)**	(−2.55)**	11.18%	5.03%
36	−1.61	(−2.64)***	(−3.09)***	16.39%	11.87%

Table AIV. Predictive Regressions where CSV has Employment-Based Weights

This table reports results of predictive regressions on future unemployment growth (Panel A) and future excess market returns (Panel B) where we use as a predictor CSV with employment-based weights, rather than equal weights as in our primary measure. Industry-level employment data are available for a set of 35 industries for the period from January 1952 to April 2003. We use the CRSP data on individual stocks to create value-weighted returns on 35 matched industry equity portfolios. Similar to our main measure, we estimate industry idiosyncratic returns with respect to the CAPM, estimated over the past 36 months. We calculate CSV based on past $m = 3$, 12 and 24-month industry-specific returns. We run the following predictive regressions:

$$y_{t:t+k} = \alpha + \beta CSV_t^m + \varepsilon_{t:t+k},$$

where $y_{t:t+k}$ is either the k-month ahead unemployment growth or the continuously compounded k-month excess return on the market from month t to month $t+k$. CSV_t^m is the cross-sectional volatility of past m-month industry idiosyncratic returns. Panel A reports the regression coefficient estimate, the corresponding Newey-West (1987) adjusted (based on $k-1$ lags) t-ratios and the in-sample R^2s. In addition, Panel B reports Hodrick (1992) t-ratios and the out-of-sample R^2. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Predicting Aggregate Unemployment Growth

	$m = 3$			$m = 12$		
k	$\hat{\beta}$	t-ratio	R^2_{IS}	$\hat{\beta}$	t-ratio	R^2_{IS}
1	0.15	$(1.80)^{*}$	0.47%	0.03	(0.63)	0.05%
3	0.29	(1.21)	0.43%	0.01	(0.12)	0.00%
12	0.98	(1.04)	0.68%	0.22	(0.35)	0.13%
24	2.61	$(2.03)^{**}$	2.68%	1.15	(1.26)	1.93%
36	2.75	$(1.81)^{*}$	2.30%	1.68	(1.36)	3.16%

	$m = 24$		
k	$\hat{\beta}$	t-ratio	R^2_{IS}
1	0.01	(0.26)	0.01%
3	−0.01	(−0.12)	0.00%
12	0.05	(0.14)	0.02%
24	0.45	(0.56)	0.74%
36	0.97	(0.98)	2.97%

Table AIV - continued

Panel B: Predicting Excess Stock Market Returns					
		$m = 3$			
k	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
1	-0.04	(-0.36)	(-0.35)	0.02%	-0.45%
3	-0.48	(-1.63)	$(-2.13)^{*}$	1.24%	0.39%
12	-2.43	$(-2.39)^{**}$	$(-3.99)^{***}$	7.35%	6.99%
24	-4.72	$(-3.01)^{***}$	$(-5.12)^{***}$	14.80%	17.63%
36	-5.63	$(-3.92)^{***}$	$(-4.02)^{***}$	14.65%	17.95%
		$m = 12$			
k	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
1	-0.08	(-1.49)	(-1.52)	0.41%	0.20%
3	-0.34	$(-2.13)^{**}$	$(-2.79)^{***}$	2.19%	1.98%
12	-1.15	$(-2.16)^{**}$	$(-3.09)^{***}$	6.03%	6.66%
24	-2.72	$(-3.10)^{***}$	$(-4.34)^{***}$	18.24%	16.49%
36	-3.03	$(-2.48)^{**}$	$(-3.35)^{***}$	15.61%	12.07%
		$m = 24$			
k	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
1	-0.04	(-1.38)	(-1.38)	0.32%	0.03%
3	-0.18	$(-1.99)^{**}$	$(-2.51)^{**}$	1.74%	0.91%
12	-0.72	$(-2.18)^{**}$	$(-2.61)^{***}$	6.18%	2.87%
24	-1.40	$(-2.07)^{**}$	$(-3.50)^{***}$	12.14%	1.22%
36	-2.04	$(-2.18)^{**}$	$(-3.89)^{***}$	20.10%	4.91%

Table AV. Predictive Regressions where CSV has Market Capitalization-Based Weights

This table reports results of predictive regressions on future unemployment growth (Panel A) or future excess market returns (Panel B) where our predictor is CSV (for 49 industries) with market capitalization-based weights, rather than equal weights as in our primary measure. We run the following predictive regressions:

$$y_{t:t+k} = \alpha + \beta CSV_t^m + \varepsilon_{t:t+k},$$

where $y_{t:t+k}$ is either the k-month ahead unemployment growth or the continuously compounded k-month excess return on the market from month t to month $t+k$. CSV_t^m is the market capitalization weighted cross-sectional volatility of past m-month industry idiosyncratic returns. Panel A reports the regression coefficient estimate, the corresponding Newey-West (1987) adjusted (based on $k-1$ lags) t-ratios and the in-sample R^2s. In addition, Panel B reports Hodrick (1992) t-ratios and the out-of-sample R^2,. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Predicting Aggregate Unemployment Growth

	$m=3$			$m=12$		
k	$\hat{\beta}$	t-ratio	R^2_{IS}	$\hat{\beta}$	t-ratio	R^2_{IS}
1	0.24	(3.30)***	1.63%	0.07	(1.94)*	0.56%
3	0.60	(2.90)***	2.58%	0.19	(1.83)*	1.15%
12	1.62	(1.72)*	2.46%	0.58	(1.28)	1.42%
24	2.25	(1.74)*	2.36%	1.28	(2.23)**	3.49%
36	2.10	(1.39)	1.55%	1.34	(1.76)*	2.84%

	$m=24$		
k	$\hat{\beta}$	t-ratio	R^2_{IS}
1	0.02	(1.04)	0.16%
3	0.06	(0.95)	0.23%
12	0.15	(0.62)	0.22%
24	0.56	(1.38)	1.5%
36	0.65	(1.31)	1.49%

Table AV - continued

Panel B: Predicting Excess Stock Market Returns					
		$m = 3$			
k	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
1	-0.16	(-1.64)	(-1.61)	0.52%	0.02%
3	-0.38	(-1.55)	$(-1.87)^{*}$	0.93%	-0.21%
12	-1.68	$(-2.01)^{**}$	$(-2.60)^{***}$	4.26%	1.71%
24	-3.12	$(-2.17)^{**}$	$(-2.63)^{***}$	7.95%	5.17%
36	-3.63	$(-1.89)^{*}$	$(-2.22)^{**}$	8.02%	4.58%
		$m = 12$			
k	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
1	-0.09	$(-2.23)^{**}$	$(-2.29)^{**}$	0.85%	0.51%
3	-0.30	$(-2.50)^{**}$	$(-3.33)^{***}$	2.63%	1.7%
12	-1.12	$(-2.54)^{**}$	$(-4.18)^{***}$	8.54%	8.73%
24	-2.06	$(-2.70)^{***}$	$(-4.89)^{***}$	15.45%	16.40%
36	-2.15	$(-2.13)^{**}$	$(-3.05)^{***}$	12.56%	10.17%
		$m = 24$			
k	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
1	-0.05	$(-1.93)^{*}$	$(-1.98)^{**}$	0.58%	0.24%
3	-0.15	$(-1.97)^{**}$	$(-2.76)^{***}$	1.57%	0.76%
12	-0.67	$(-2.23)^{**}$	$(-4.16)^{***}$	6.72%	6.91%
24	-1.17	$(-2.43)^{**}$	$(-3.77)^{***}$	11.02%	10.26%
36	-1.49	$(-2.37)^{**}$	$(-3.44)^{***}$	13.41%	11.14%

Table AVI. Predictive Regressions where CSV is based on Total Industry Returns

This table reports results of predictive regressions on future unemployment growth (Panel A) or future excess market returns (Panel B) where our predictor variable CSV is based on total rather than idiosyncratic industry returns (for 49 industries) over the past 12 months ($m = 12$). We run the following predictive regressions:

$$y_{t:t+k} = \alpha + \beta CSV_t + \varepsilon_{t:t+k},$$

where $y_{t:t+k}$ is either the k-month ahead unemployment growth or the continuously compounded k-month excess return on the market from month t to month $t+k$. CSV_t is the equally weighted cross-sectional volatility of past 12-month compounded total industry returns. Panel A reports the regression coefficient estimate, the corresponding Newey-West (1987) adjusted (based on $k-1$ lags) t-ratios and the in-sample R^2s. In addition, Panel B reports Hodrick (1992) t-ratios and the out-of-sample R^2. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Predicting Aggregate Unemployment Growth

k	$\hat{\beta}$	t-ratio	R^2_{IS}
1	−0.02	(−0.86)	0.08%
3	−0.05	(−0.73)	0.16%
12	−0.03	(−0.07)	0.00%
24	0.47	(0.90)	0.76%
36	0.73	(1.24)	1.38%

Panel B: Predicting Excess Stock Market Returns

k	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
1	−0.06	(−2.14)**	(−2.10)**	0.62%	0.45%
3	−0.28	(−3.25)***	(−4.37)***	3.81%	3.79%
12	−0.93	(−3.34)***	(−3.86)***	9.92%	11.02%
24	−1.71	(−3.49)***	(−4.82)***	17.93%	16.81%
36	−1.98	(−3.03)***	(−4.06)***	17.93%	13.33%

Table AVII. Predictive Regressions where CSV is based on Individual Stock Returns

This table reports results of predictive regressions on future unemployment growth (Panel A) or future excess market returns (Panel B) where our predictor variable CSV is based on total returns on individual stocks rather than idiosyncratic returns on 49 industry portfolios. We use stock returns from CRSP for all stocks traded on the NYSE, AMEX and Nasdaq. We run the following predictive regressions:

$$y_{t:t+k} = \alpha + \beta CSV_t + \varepsilon_{t:t+k},$$

where $y_{t:t+k}$ is either the k-month ahead unemployment growth or the continuously compounded k-month excess return on the market from month t to month $t+k$. CSV_t is the equally or market capitalization weighted cross-sectional volatility of past 12-month compounded total returns on individual stocks. Panel A reports the regression coefficient estimate, the corresponding Newey-West (1987) adjusted (based on $k-1$ lags) t-ratios and the in-sample R^2s. In addition, Panel B reports Hodrick (1992) t-ratios and the out-of-sample R^2. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Predicting Aggregate Unemployment Growth

	Equally weighted			Value weighted		
k	$\hat{\beta}$	t-ratio	R^2_{IS}	$\hat{\beta}$	t-ratio	R^2_{IS}
1	−0.02	(−3.76)***	1.70%	−0.01	(−2.57)***	0.69%
3	−0.05	(−3.24)***	3.47%	−0.04	(−2.29)**	1.25%
12	−0.15	(−2.06)**	4.11%	−0.07	(−0.79)	0.55%
24	−0.16	(−1.23)	2.37%	0.05	(0.32)	0.13%
36	−0.14	(−0.93)	1.36%	0.14	(0.85)	0.77%

Panel B: Predicting Excess Stock Market Returns

		Equally weighted			
k	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
1	−0.01	(−1.17)	(−1.15)	0.17%	−0.56%
3	−0.02	(−1.52)	(−1.97)**	0.79%	−0.78%
12	−0.09	(−1.52)	(−1.55)	2.32%	−2.97%
24	−0.18	(−1.91)*	(−1.83)*	5.36%	−12.75%
36	−0.20	(−1.64)	(−1.41)	5.07%	−24.74%
		Value weighted			
k	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
1	−0.01	(−1.56)	(−1.55)	0.40%	−0.65%
3	−0.05	(−1.87)*	(−2.77)***	1.55%	−0.72%
12	−0.19	(−2.00)**	(−3.49)***	6.14%	1.73%
24	−0.39	(−2.26)**	(−5.42)***	13.06%	1.09%
36	−0.49	(−2.21)**	(−5.26)***	16.17%	−4.04%

Table AVIII. Predictive Regressions where CSV is based on 100 Size and BM Ranked Portfolios

This table reports results of predictive regressions on future unemployment growth (Panel A) or future excess market returns (Panel B) where our predictor variable CSV is based on idiosyncratic returns on 100 size and book-to-market ranked portfolios rather than 49 industry portfolios. We run the following predictive regressions:

$$y_{t:t+k} = \alpha + \beta CSV_t + \varepsilon_{t:t+k},$$

where $y_{t:t+k}$ is either the k-month ahead unemployment growth or the continuously compounded k-month excess return on the market from month t to month $t+k$. CSV_t is the equally weighted cross-sectional volatility of past 12-month compounded idiosyncratic returns on 100 size and book-to-market ranked portfolios. Panel A reports the regression coefficient estimate, the corresponding Newey-West (1987) adjusted (based on $k-1$ lags) t-ratios and the in-sample R^2s. In addition, Panel B reports Hodrick (1992) t-ratios and the out-of-sample R^2. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Predicting Aggregate Unemployment Growth

k	$\hat{\beta}$	t-ratio	R^2_{IS}
1	0.03	(0.79)	0.07%
3	0.10	(0.99)	0.22%
12	0.65	(1.30)	1.19%
24	1.33	(1.73)*	2.45%
36	1.30	(1.17)	1.78%

Panel B: Predicting Excess Stock Market Returns

k	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
1	−0.12	(−2.25)**	(−2.17)**	0.86%	0.63%
3	−0.40	(−2.67)***	(−3.78)***	3.12%	3.15%
12	−1.22	(−2.32)**	(−3.65)***	6.75%	6.55%
24	−1.95	(−2.12)**	(−2.81)***	9.27%	4.75%
36	−1.95	(−1.58)	(−2.10)**	6.96%	1.42%

Table AIX. Predictive Regressions for Different Subsample Periods

This table reports results of predictive regressions on future unemployment growth (Panel A) or future excess market returns (Panel B) for three different subsample periods: from January 1973 to December 2019, from January 1952 to December 1985 and from January 1986 to December 2019. We run the following predictive regressions:

$$y_{t:t+k} = \alpha + \beta CSV_t + \varepsilon_{t:t+k},$$

where $y_{t:t+k}$ is either the k-month ahead unemployment growth or the continuously compounded k-month excess return on the market from month t to month $t+k$. CSV_t is the equally weighted cross-sectional volatility of past 12-month compounded idiosyncratic returns on 49 industry portfolios. Panel A reports the regression coefficient estimate, the corresponding Newey-West (1987) adjusted (based on $k-1$ lags) t-ratios and the in-sample R^2s. The final column reports the correlation between the log excess stock market returns and unemployment growth, where both are taken over the same k-month horizon. In addition, Panel B reports Hodrick (1992) t-ratios and the out-of-sample R^2. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Predicting Aggregate Unemployment Growth

		1973:01–2019:12		
k	$\hat{\beta}$	t-ratio	R^2_{IS}	$\text{corr}(r_{M,t:t+k}, \Delta un_{t:t+k})$
1	0.12	(3.79)***	3.41%	−0.03
3	0.36	(4.04)***	8.53%	−0.12
12	1.25	(2.85)***	11.42%	−0.39
24	1.99	(3.64)***	11.11%	−0.59
36	1.89	(2.44)**	6.59%	−0.67
		1952:01–1985:12		
k	$\hat{\beta}$	t-ratio	R^2_{IS}	$\text{corr}(r_{M,t:t+k}, \Delta un_{t:t+k})$
1	0.06	(0.93)	0.25%	0.01
3	0.09	(0.39)	0.13%	0.01
12	−0.01	(−0.01)	0.00%	−0.08
24	0.51	(0.41)	0.38%	−0.13
36	0.39	(0.32)	0.22%	−0.19
		1986:01–2019:12		
k	$\hat{\beta}$	t-ratio	R^2_{IS}	$\text{corr}(r_{M,t:t+k}, \Delta un_{t:t+k})$
1	0.1	(2.95)***	2.68%	−0.08
3	0.32	(4.18)***	9.21%	−0.24
12	1.37	(3.13)***	18.51%	−0.53
24	2.00	(3.27)***	13.36%	−0.68
36	2.08	(2.31)**	8.59%	−0.73

Table AIX - continued

Panel B: Predicting Excess Stock Market Returns					
		1973:01–2019:12			
k	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
1	−0.09	(−1.96)**	(−1.98)**	0.79%	1.08%
3	−0.36	(−2.61)***	(−3.38)***	4.25%	7.09%
12	−1.39	(−2.74)***	(−4.18)***	15.21%	22.44%
24	−2.05	(−2.52)**	(−3.70)***	19.78%	22.56%
36	−2.19	(−2.06)**	(−2.83)***	16.82%	18.14%
		1952:01–1985:12			
k	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
1	−0.04	(−0.68)	(−0.68)	0.15%	−0.83%
3	−0.19	(−1.07)	(−1.32)	0.93%	−2.97%
12	−0.79	(−1.34)	(−1.63)	3.39%	−1.64%
24	−1.92	(−2.01)**	(−2.41)**	11.90%	4.36%
36	−1.71	(−1.46)	(−1.74)*	7.55%	−14.59%
		1986:01–2019:12			
k	$\hat{\beta}$	t-ratio$_{Hodr}$	t-ratio$_{NW}$	R^2_{IS}	R^2_{OOS}
1	−0.12	(−2.40)**	(−2.42)**	1.58%	1.39%
3	−0.46	(−3.00)***	(−4.00)***	7.99%	6.56%
12	−1.64	(−2.80)***	(−4.90)***	25.27%	15.20%
24	−2.22	(−2.24)**	(−3.50)***	23.17%	−6.33%
36	−2.75	(−2.08)**	(−3.32)***	23.90%	−10.99%