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The cross-sectional return predictability of employment growth: A liquidity risk explanation

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Abstract

Employment growth (EG) is related to liquidity fundamentals of investment opportunities, firm health, and information environment and quality. This, in turn, implies that liquidity risk may play a role in explaining the relation between employment growth and stock returns. We find strong empirical evidence supporting the link between employment growth and liquidity risk. Stocks of high-EG firms are more liquid and exposed to lower liquidity risk than stocks of low-EG firms. After adjusting for liquidity risk, employment growth loses its power to predict returns.

1. INTRODUCTION

Belo et al. (2014) is the first study to examine the relation between firms' employment growth (EG) and their stock returns. They find that EG predicts stock returns and argue that the negative relation between them reflects the shock to the labor adjustment costs. In this paper, we show that liquidity risk explains the EG-return relationship.[1]

In our study, we conjecture that liquidity risk has the potential to explain the return predictability of EG. On the one hand, liquidity risk appears to be a priced state variable important for asset pricing. Studies show that investors require a premium to compensate for their exposure to liquidity risk (e.g., Pastor and Stambaugh, 2003; Liu, 2006; Sadka, 2006; and Amihud and Noh, 2020).[2] On the other hand, a firm's hiring and firing activities are likely related to its investment opportunities, health conditions (such as financial constraints and/or distress), [3] and information environment and quality, which are fundamental sources affecting stock liquidity (Liu, 2006; Lang et al. (2012); Kerr et al., 2020).

Our results confirm the association between a firm's EG and liquidity fundamentals. As expected, EG is related to firm's financial health: low-EG firms appear to be financially distressed

[1]Prior studies have reported a positive association of market liquidity with labor market employment (Levine and Zervos, 1998; Næs et al., 2011; Rocheteau and Rodriguez-Lopez, 2014; Yépez, 2017). Gomis-Porqueras (2020) shows that labor market conditions affect asset prices in the presence of illiquidity. Thus, the return predictability associated with the changes in firm's employment is likely related to variations in market liquidity. Recent studies also highlight the role of labor market frictions in asset pricing, e.g., Uhlig (2007), Favilukis and Lin (2013), Belo et al. (2017), Hall (2017), Kilic and Wachter (2018), Donangelo et al. (2019), and Belo et al. (2020).

[2]Chan and Faff (2005) show supporting evidence for a liquidity-augmented Fama-French model in Australian. Cheng et al. (2013) highlight the role of liquidity risk in real estate markets. Liu et al. (2016) find that liquidity risk is priced in the liquidity-extended Epstein-Zin Model.

[3]Asness et al. (2000) show that firms that have recently cut jobs are in distress. Brown and Matsa (2016) find that an increase in an employer's financial distress leads to fewer and lower quality job seekers. These results provide support to our liquidity-risk based explanation as liquidity risk captures distress risk (Liu, 2006). The link of liquidity to labor hiring is also related to prior research showing that firms with higher leverage ratios are likely to cut employees (e.g., Sharpe, 1994; Hanka, 1998) and that illiquid stocks have high leverage ratios (e.g., Fang et al., 2009).

or constrained whereas high-EG firms tend to be financially healthier. A firm's EG is positively related to Tobin's q, investment rate, and asset growth, indicating more investment opportunities for high-EG firms as compared to low-EG firms. A firm's EG is also positively correlated with information measures such as the number of institutional investors, institutional ownership, advertising growth, and earnings quality, meaning a lower level of information asymmetry for high-EG firms than for low-EG firms. This evidence suggests that high-EG firms are likely to be more liquid and, hence, exposed to lower liquidity risk than are low-EG firms.

Indeed, using different liquidity proxies, we observe that low-EG stocks are thinly and infrequently traded compared to high-EG stocks, and trading on low-EG stocks incurs high transaction costs and has large impact on price as compared to trading on high-EG stocks. The liquidity betas of the Liu (2006) liquidity-augmented CAPM (LCAPM) decrease steadily and almost monotonically from low- to high-EG portfolios (Figure 1). This pattern is largely consistent throughout the paper, which demonstrates the impact of EG on liquidity risk. After taking into account of the two risk sources (market and liquidity) of the LCAPM, we find that the power of EG in predicting stock returns diminishes. Yet non-liquidity-based pricing models such as the CAPM, the Fama and French (1993) three-factor model (FF3FM), the momentum-extended FF3FM, the Fama and French (2015) five-factor model (FF5FM), and the Hou et al. (2015) q-factor model (HXZqFM) are not capturing the EG effect. Consistent with our conjecture, the EG return predictability stems from the liquidity risk.

We perform various robustness tests to check our results. We examine the performance of portfolios formed by sequential double sorts on investment rate and EG, and on industry competition/transparency and EG; we separately examine NYSE/AMEX and NASDAQ stocks;

we test results in subperiods including periods of recessions and periods of decimalization of stock prices. Our main results are consistent throughout these tests.

The ability of liquidity risk in explaining the EG-return relation is economically intuitive. Firms with high EG are expanding (owing to more investment opportunities, for example), are healthier, are more transparent, and have higher earnings quality. These firms are more attractive to investors and, thus, are more liquid than firms with low EG. When the economy is haunted by uncertainty and liquidity squeeze, the returns of high-EG firms are less sensitive to liquidity shocks than those of low-EG firms. As a result, they relieve investors from states of negative economic shocks while low-EG firms undermine investors' ability to cushion the deterioration in economic conditions. Consequently, investors require high returns to hold securities of low-EG firms due largely to their exposure to high liquidity risk.

Our study makes several contributions to the literature. First, we provide a liquidity risk explanation to the cross-sectional return predictability of EG (Belo, et al., 2014). Second, we extend the aggregate relation between unemployment rate and liquidity of Næs et al. (2011) by showing novel evidence at the firm level. Third, we extend previous studies on the importance of liquidity in firms' health such as distress risk (Liu, 2006), credit risk (Das and Hanouna, 2009), leverage (Fang et al., 2009), and information quality (Ng, 2011).

The remainder of the paper proceeds as follows. In Section 2, we describe the data. In Section 3, we conduct empirical analyses and perform robustness tests. Finally, Section 4 concludes the paper.

2. DATA AND DESCRIPTIVE STATISTICS

Our sample contains NYSE/AMEX/ARCA/NASDAQ ordinary common stocks (i.e., stocks with a CRSP share code 10 or 11) over 1964–2014.[4] We exclude utility and financial firms, which have four-digit standard industrial classification (SIC) codes between 4900 and 4999, and between 6000 and 6999. We collect data of monthly stock returns, daily returns, daily trading volumes, daily prices per share from CRSP.[5] We measure monthly market capitalizations of sample stocks using price per share and the number of shares outstanding from CRSP. Using COMPUSTAT annual data, we follow Davis et al. (2000) to calculate firms' book equity values.[6] We also calculate the book-equity-deflated operating profitability (OP) and the total asset growth rate (AG) as in Fama and French (2015).

We calculate the employment growth (EG) in the same way as in Belo et al. (2014):

$$EG_{i,t} = \frac{(EMP_{i,t} - EMP_{i,t-1})}{0.5 \times (EMP_{i,t-1} + EMP_{i,t})} \tag{1}$$

where $EMP_{i,t}$ is the number of employees of firm i in fiscal year t (COMPUSTAT mnemonic code: EMP). As in Belo et al. (2014), the investment rate for firm i in fiscal year t is:

$$IK_{i,t} = \frac{(CAPX_{i,t} - SPPE_{i,t-1})}{0.5 \times (PPENT_{i,t-1} + PPENT_{i,t})} \tag{2}$$

[4]Similar to Belo et al. (2014), we do not include the pre-1964 period because accounting data of many firms from COMPUSTAT are not available in the early period.

[5]We make adjustments to delisting returns. If a delisted stock's delisting return is missing, we follow Shumway (1997) and Shumway and Warther (1999) and assume a delisting return of -1 for delisting due to liquidation (CRSP delisting codes 400–490), -0.33 for performance related delisting (CRSP codes 500 and 520–584), and zero otherwise.

[6]In using COMPUSTAT annual data, we assume that they are available to public five months after the fiscal year end date.

where $CAPX$ is the COMPUSTAT mnemonic code for capital expenditures, $SPPE$ for sale of property, plant, and equipment, and $PPENT$ for property, plant and equipment.[7]

We use four liquidity measures with each highlighting one of the four dimensions of liquidity: trading quantity, the impact of trading on price, trading speed, and trading costs. Specifically, the four liquidity measures are:

(i) The dollar volume measure of Brennan et al. (1998), DV, defined as the daily dollar volume averaged over the previous 12 months.

(ii) The price impact measure of Amihud (2002), RV, defined as the daily absolute-return-to-dollar-volume ratio averaged over the previous 12 months.

(iii) The trading discontinuity measure of Liu (2006), LM, defined as the standardized turnover-adjusted number of zero daily trading volumes over the previous 12 months,

$$LM = \left[\textit{Number of zero daily volumes in prior } 12 \textit{ months} + \frac{1/(12\textit{-month turnover})}{20{,}000} \right] \times \frac{21 \times 12}{NoTD}, \quad (3)$$

where 12-*month turnover* is the sum of daily turnover (in percentage) over the previous 12 months, $NoTD$ is the total number of exchange trading days over the previous 12 months, and 20,000 is chosen so that $0 < \frac{1/(12\textit{-month turnover})}{20{,}000} < 1$ for all sample stocks. The factor $21 \times 12/NoTD$ standardizes the number of monthly trading days in the market to 21, which makes the LM values comparable over time. The LM measure captures the probability of no trading. Large LM (i.e., high infrequent trading) indicates low liquidity.[8]

[7]We exclude stocks with missing or negative $PPENT$, missing EMP, and missing $CAPX$.

[8]Similar to Amihud (2002), the calculation of RV requires that there are at least 80% nonmissing daily trading volumes available in the prior 12 months. Also, the calculation of RV excludes zero trading volumes. Constructions of DV and LM require no missing daily trading volumes in the prior 12 months.

(iv) The bid-ask spread estimate of Corwin and Schultz (2012), *CS*. For each month, they estimate the bid-ask spread using daily high and low prices in that month. The *CS* measure is the average of the Corwin and Schultz (2012) estimates over the previous 12 months.[9]

As illustrated in Liu (2006), liquidity stems from economic conditions (or investment opportunities), information environment, and firm's health, i.e., deteriorations in these reduce liquidity. Better information environment (or less information asymmetry) is related to shareholder base, media coverage, analysts coverage, and advertising, etc. Firm health is associated with financial distress and/or constraints. To ascertain whether a firm's EG is related to those liquidity fundamentals, we use the number of institutional investors, institutional ownership, and advertising growth rate to proxy for information environment, and we use leverage and the Whited and Wu (2006) financial constraints index (WWindex) to proxy for firm's financial health.[10]

We calculate advertising growth rate (*ADG*) using Advertising Expense (COMPUSTAT mnemonic code: XAD). To calculate the number of institutional investors and institutional ownership, we draw data from the Thomson Financial Institutional Holdings (13F) database. The variable *Leverage* is the market leverage, as defined in Gomes and Schmid (2010):

$$Leverage = \frac{\text{Book Debt}}{\text{Book Debt} + MV}, \tag{4}$$

[9] We thank Shane Corwin for sharing with us their high-low-price-based bid-ask spread estimates.

[10] Purnanandam (2008) uses leverage to proxy for financial distress, i.e., high leverage is more likely to indicate financial distress. Whited and Wu (2006) show that their index characterizes firm's financial constraints better than the commonly used Kaplan and Zingales (1997) index.

where Book Debt is the difference between total asset value and book value of equity, and MV is the market capitalization. The firm's WWindex in a given year is calculated as follows:

$$WWindex = -0.091CF - 0.062DIVPOS + 0.021TLTD - 0.044LNTA + 0.102ISG - 0.035SG, \quad (5)$$

where CF is the ratio of cash flow $(IB + DP)$ to total assets (AT); $DIVPOS$ is an indicator that takes the value of one if the firm pays cash dividends $(DVP + DVC)$, and zero otherwise; $TLTD$ is the ratio of long-term debt $(DLTT + DLC)$ to total assets; $LNTA$ is the natural logarithm of total asset; ISG is the industry sales growth based on the three-digit SIC code; and SG is the sales $(SALE)$ growth.

Further, market-makers' intention to provide liquidity in market downturn plays an important role in the relation between EG and liquidity risk. Market-makers are more inclined to provide liquidity to high-quality (i.e., big, liquid, and low volatility) firms than low-quality firms due to "flight to quality" (Sadka, 2011; Nagel, 2012). Thus, compared to low-EG firms, high-EG firms (big and high earnings quality) are likely to be more attractive to market-makers, especially during market turmoils, which leads to higher liquidity and lower liquidity risk.

To test this, we measure earnings quality as accruals quality (AQ), which is the standard deviation of the residuals estimated from the following cross-sectional regression following Francis et al. (2008):

$$\begin{aligned}\frac{TCA_{i,t}}{Asset_{i,t}} = \phi_{0,i} + \phi_{1,i}\frac{CFO_{i,t-1}}{Asset_{i,t}} + \phi_{2,i}\frac{CFO_{i,t}}{Asset_{i,t}} + \phi_{3,i}\frac{CFO_{i,t+1}}{Asset_{i,t}} \\ + \phi_{4,i}\frac{\Delta Rev_{i,t}}{Asset_{i,t}} + \phi_{5,i}\frac{PPE_{i,t}}{Asset_{i,t}} + \upsilon_{i,t},\end{aligned} \quad (6)$$

where $TCA = \Delta CA - \Delta CL - \Delta Cash + \Delta STDebt$ is total current accruals, $CFO = NIBE - TA$ is firm i's cash flow from operations, $NIBE$ is firm i's net income before extraordinary items (item IB), $TA = (\Delta CA - \Delta CL - \Delta CASH + \Delta STDebt - \Delta DEPN)$ is firm i's total accruals, ΔCA is firm i's change in current assets (item ACT), ΔCL is firm i's change in current liabilities (item LCT), $\Delta Cash$ is firm i's change in cash (item CHE), $\Delta STDebt$ is firm i's change in debt in current liabilities (item DCL), $\Delta DEPN$ is firm i's depreciation and amortization expense (item DP), ΔRev is firm i's change in revenues (item $SALE$), PPE is firm i's gross value of plant, property, and equipment (item $PPEGT$), and $ASSET$ is total asset. The standard deviation of the residuals is calculated from year $t-9$ to t for each firm. High AQ is associated with low accruals quality.

Table 1 provides descriptive statistics for the main variables. Because of the different recording methods on trading volumes between NYSE/AMEX/ARCA and NASDAQ stocks, we report the statistics separately for the two groups.[11] For NYSE/AMEX/ARCA stocks, the average employment growth (EG) is 3.374% per annum over 1964–2013; while it is 6.562% per annum for NASDAQ stocks over 1984–2013.[12] In line with Asness et al. (2000) and Belo et al. (2014), EG is positively correlated with firm size (MV) and negatively correlated with book-to-market (B/M). The correlations between EG and operating profitability (OP), asset growth rate (AG), and investment rate (IK) are positive, suggesting that high-EG firms are more profitable and have more investment opportunities.

[Table 1 about here]

[11]Compared to NYSE/AMEX/ARCA stocks, trading volumes of NASDAQ stocks are inflated due to intra-dealer transactions.

[12]For NASDAQ stocks, daily trading volume data become available from the beginning of November 1982.

The correlations between EG and financial health variables are also consistent with our expectation. The correlations of EG with both *Leverage* and *WWindex* are negative, implying that high-EG firms tend to be less financially distressed/constrained than low-EG firms. We also observe positive correlations between EG and information variables such as advertising growth (ADG), the number of institutional investors (*NoInst*), and institutional ownership (*InstOwn*), indicating that high-EG firms are more transparent than low-EG ones. Further, the negative correlation between EG and accrual quality (AQ) suggests that high-EG firms have higher information quality than do low-EG firms. Consistent with our conjecture, EG is positively correlated with the liquidity proxy (DV) and negatively correlated with the illiquidity proxies (RV, LM, and CS). This evidence shows that, compared to high-EG stocks, low-EG stocks tend to have low trading volumes, large price impact, slow trading speed, and high trading costs.

Table 2 reports key characteristics of EG decile portfolios formed at the end of June each year. For trading volume-based liquidity measures, we report those characteristics separately for the NYSE/AMEX/ARCA and NASDAQ stocks.[13] Table 2 shows that the investment rate (IK) and asset growth rate (AG) increase monotonically from low- to high-EG portfolios, indicating that high-EG firms expand more. Low-EG firms, on average, cut 32.91% of their labor force while high-EG firms employ 43.66% more. Low-EG firms tend to be small, distressed, and unprofitable (smallest MV, highest B/M, and lowest OP). Moreover, high-EG firms have higher advertising growth (ADG), larger institutional holdings (*NoInst* and *InstOwn*), are less financially distressed/constrained (low *Leverage* and *WWindex*), and have higher earnings qual-

[13] As stated in Table 1, because of the different recording methods on trading volumes between NYSE/AMEX/ARCA and NASDAQ stocks, we report separately for the two groups.

ity (AQ) than low-EG firms. In terms of liquidity, high-EG firms are more liquid than low-EG firms, regardless of the choices of liquidity measures used.

Figure 1 depicts the discontinuity measure of liquidity (i.e., liquidity as a firm characteristic), LM, for the EG deciles. It shows that liquidity steadily improves along with firms' EG rates, suggesting that liquidity is likely to play a significant role in explaining the EG-return relation.

[Table 2 about here]

[Figure 1 about here]

A firm's shares can become less liquid for at least four reasons: (1) severe information asymmetry, (2) deteriorated firm health, (3) poor investment opportunities, and (4) economic downturns.[14] We investigate further the relation between EG and the liquidity fundamentals by performing a partial correlation analysis using the Fama–MacBeth (1973) cross-sectional regression:

$$EG_{i,t} = \delta_0 + \delta_1 \times \mathit{InvestmentOpportunity}_{i,t} + \delta_2 \times \mathit{Information}_{i,t} + \delta_3 \times \mathit{FirmHealth}_{i,t} + e_{i,t}, \quad (7)$$

where we use investment rate (IK) and asset growth (AG) to proxy for *InvestmentOpportunity*; advertising growth rate (ADG), the number of institutional investors (*NoInst*), institutional ownership (*InstOwn*), and accrual quality (AQ) for *Information*; and book-to-market ratio (*B/M*), leverage (*Leverage*), and Whited and Wu (2006) financial constraints index ($WWindex$) for $FirmHealth$.

Increasing in investment opportunities is likely to create more positions and to raise labor hiring while, in contrast, we normally observe workforce reductions during economic downturns

[14] The last two can be related to each other, e.g., bad market conditions usually lead to reduced investment opportunities.

that, in turn, generally lead to less investment opportunity. For instance, Cingano et al. (2016) find that following the 2008 financial crisis, firms' investment and employment fell substantially. Accordingly, investment/growth opportunities are likely to have a positive impact on employment growth. Financially distressed/constrained firms would have difficulties in financing additional jobs and may even lay off employees (e.g., Sharpe, 1994; Hanka, 1998; Falato and Liang, 2016), creating a downward pressure on labor hiring. In terms of information and EG, Rees (1966) argues that "the richness and reliability of the information" plays an important role in labor hiring. Whitaker (1999) finds that the change in employees is positively correlated with the change in advertising. We, thus, expect that more transparent firms attract more candidates and promote hiring.

Consistent with our predictions, Table 3 shows that EG is positively correlated with capital expenditure (i.e., positive coefficients on IK and AG), negatively correlated with financial distress/constraints (i.e., negative coefficients on B/M, *Leverage*, and *WWindex*), and positively related to firm's information environment and quality (i.e., positive coefficients on ADG, *NoInst*, *InstOwn*, and AQ). These results imply that, compared to high-EG firms, low-EG firms tend to be more financially distressed/constrained, invest less, face more asymmetric information problems, and have higher earnings quality.

[Table 3 about here]

Overall, our regression results are consistent with the correlation analysis in Table 1 and the characteristics of EG portfolios in Table 2. The association of firm employment growth with liquidity fundamentals underpins our conjecture that liquidity risk has a potential power in explaining the EG-return relation.

3. EMPIRICAL RESULTS

3.1 Return predictability of EG

We adopt the common approach to examine the return predictability of employment growth: portfolio analysis. Specifically, we form equal-weighted portfolios with NYSE breakpoints at the end of June each year and hold the portfolios for the subsequent 12 months. We calculate the monthly portfolio returns over the 12-month holding period based on the decomposed buy-and-hold method of Liu and Strong (2008).

In addition to the monthly raw portfolio returns, we also measure portfolio performance based on several asset pricing models including the Fama–French (1993) three-factor model (FF3FM), the Carhart (1997) momentum-extended FF3FM, the Pastor and Stambaugh (2003) liquidity-extended FF3FM, the Liu (2006) liquidity-augmented capital asset pricing model (LCAPM), the Hou et al. (2015) q-factor model (HXZqFM), and the Fama–French (2015) five-factor model (FF5FM).[15] Specifically, we run the following time-series regressions:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t}, \tag{8}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}, \tag{9}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,p} f_{PSF,t} + \varepsilon_{i,t}, \tag{10}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}, \tag{11}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{ME,t} + \beta_{i,r} f_{ROA,t} + \beta_{i,c} f_{I/A,t} + \varepsilon_{i,t}, \tag{12}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}, \tag{13}$$

[15] We also use the CAPM benchmark, which does not subsume the EG effect. We skip the CAPM adjusted results to preserve space.

where $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{SMB,t}$ is the month-t value of the Fama–French (FF) size factor, $f_{HML,t}$ is the month-t value of the FF book-to-market factor, $f_{RMW,t}$ is the month-t value of the FF profitability factor, $f_{CMA,t}$ is the month-t value of the FF investment factor, $f_{WML,t}$ is the month-t value of the momentum factor, $f_{PSF,t}$ is the month-t value of the Pastor–Stambaugh (PS) traded liquidity factor, $f_{LF,t}$ is the month-t value of the Liu (2006) liquidity factor, $f_{ME,t}$ is the month-t value of the Hou et al. (2015) (HXZ) size factor, $f_{ROA,t}$ is the month-t value of the HXZ profitability factor, and $f_{I/A,t}$ is the month-t value of the HXZ investment factor.

Following Clogg et al. (1995) and Cohen et al. (2013),[16] we estimate t-statistics of low-minus-high EG portfolio αs as

$$t_{\alpha_{L\text{–}H}} = \frac{\alpha_{Low} - \alpha_{High}}{\sqrt{(SE^2_{\alpha_{Low}} + SE^2_{\alpha_{High}})}}, \tag{14}$$

where SE is the standard error.[17] When we use a pricing model to estimate the α of an asset/portfolio, the hypothesis is that the model is right or $\alpha = 0$. Especially, insignificant α means that it is specific to the asset/portfolio (i.e., α is the return of the asset/portfolio after netting out the influence of the factor(s)) and is not correlated with αs of other different assets/portfolios. We estimate t-statistics of low-minus-high EG portfolio βs in the same way.

Panel A of Table 4 reports the performance of the equal-weighted decile portfolios sorted by EG. In general, raw returns decrease from low- to high-EG portfolios. The low-EG firms earn an average return of 1.220% per month and the high-EG firms earn an average return of 0.858%

[16]See Chapter 2 of Cohen et al. (2013)

[17]The t-statistics of Eq. (14) are more conservative than the conventional t-statistics. For Table 4 Panel A, for instance, the conventional t-statistics of EG premium are 2.61, 2.18, 2.78, 2.57, 2.76, and 1.31 under the FF3FM, the momentum-extended FF3FM, the PS liquidity-extended FF3FM, the FF5FM, the HXZqFM, and the LCAPM, respectively.

per month, leading to an economically and statistically significant premium of 0.363% ($t = 3.48$) per month. After we adjust for the FF3FM, the *EG* premium remains significant at 0.245% ($t = 1.91$) per month.[18]

[Table 4 about here]

Further, the *EG* premium is also significant at 0.275%, 0.232%, and 0.269% per month under the PS liquidity-extended FF3FM, the FF5FM, and the HXZqFM, respectively. Consistent with our early analyses on correlations, partial correlations, and portfolio characteristics (Tables 1–3), under the FF5FM, the loadings on the size, investment, and profitability factors indicate that low-*EG* firms are small, unprofitable, and invest less. However, the loadings on the market and book-to-market show no clear tendency to explain the *EG* premium.

In contrast, the LCAPM adjusted return, i.e., the intercept estimate of Equation (11), is generally insignificant across the *EG* decile portfolios. The loadings on the liquidity risk factor clearly show that liquidity beta decreases steadily from low- to high-*EG* portfolios (see also Figure 1). The low-*EG* portfolio loads most heavily on the liquidity risk factor at 0.454 ($t = 6.49$) and the high-*EG* portfolio's loading on the liquidity risk factor is the least and insignificant at 0.082 ($t = 1.46$), leading to a highly significant difference of 0.373 ($t = 4.16$) between the two. This is in line with our conjecture that low-EG firms are exposed to high liquidity risk as compared to high-EG firms. After we adjust for the LCAPM, low-*EG* firms no longer exhibit abnormal performance relative to high-*EG* firms, with the LCAPM-adjusted return difference between the low-*EG* portfolio and the high-*EG* portfolio being insignificant at 0.129% ($t = 0.53$) per month. The loadings of the *EG* decile portfolios on the market factor of the LCAPM display a U shape,

[18] We observe a similar α pattern as in Belo et al. (2014). For example, under the FF3FM with equal-weighted quintile portfolios, Belo et al. (2014) find that the low-*EG* portfolio α is 2.27% ($t = 1.29$) per annum and that the high-*EG* portfolio α is -6.32% ($t = -3.90$) per annum.

and the market factor loading difference between the two polar EG portfolios is small and less significant at 0.051 ($t = 0.75$). Taken together, the ability of employment growth to predict return is primarily due to liquidity risk.

The performance difference between the PS and Liu liquidity factors is likely because the two are constructed differently. The construction of the PS factor is based on the price sensitivity to trading volume, which shows insignificant liquidity premium, whereas the Liu liquidity factor is based on the trading discontinuity measure that captures multidimensions of liquidity and generates a robust liquidity premium. Further tests by Ma et al. (2021) show that the trading discontinuity-based factor captures the systematic nature of liquidity risk.

Since Belo et al. (2014) also perform tests on the equal-weighted portfolios excluding micro-cap stocks and the value-weighted portfolios, we replicate their tests on our sample. Results are reported in Panels B and C of Table 4. As can be seen, the LCAPM can still explain the EG premium for both the equal-weighted portfolios excluding micro-cap stocks and the value-weighted portfolios.[19]

3.2 Robustness on subsamples and subperiods

To check the robustness of our main results, we conduct subsample and subperiod analyses. For the subsample investigation, we split the full sample into three investment rate (IK) based subsamples, similar to Belo et al. (2014).[20] Within each IK subsample, we form EG quintile portfolios with NYSE breakpoints at the end of June each year and hold the portfolios for the

[19]Since Panels B and C show similar results to Panel A, we report only the equal-weighted results to preserve space in the rest of the paper.

[20]While firms can be subject to other adjustment costs such as advertising during a demand shock, we also split the full sample into advertising expenditure growth and asset growth subsamples. Our results are similar in these tests.

subsequent 12 months. Similar to Fama and French (2008), the sorts on EG use the same NYSE breakpoints for all three IK subsamples in order to have meaningful comparisons of returns across the IK subsamples.

Results in Table 5 show that the EG premium becomes smaller after controlling for IK. Before any risk adjustment, the EG premiums are significant at 0.194% and 0.285% per month in low- and high-IK subsamples, respectively. The LCAPM explains the EG premium for all three IK subsamples. For the high-EG subsample, for instance, the LCAPM-adjusted return difference between the low- and the high-EG portfolios is 0.122% ($t = 0.51$) per month. For each subsample, the loadings on the liquidity risk factor decrease significantly from the low- to high-EG portfolios, while the loading differences on the market factor of the LCAPM are insignificant between the low- and the high-EG portfolios. These results again suggest that liquidity risk plays a central role in explaining the return predictability of employment growth.

[Table 5 about here]

For the subperiod analysis, we evenly divide the full sample horizon into two 25-year subperiods. For each subperiod, we form EG decile portfolios with NYSE breakpoints at the end of June each year and hold the portfolios for the subsequent 12 months. Table 6 shows that the EG effect is not actually robust in the first 25 years (1964–1989), which is true either before or after any risk adjustment. For the recent 25 years (1989–2014), the EG premium is 0.503% ($t = 3.20$) per month before any risk adjustment and robust to the FF3FM, the momentum-extended FF3FM, the PS liquidity-extended FF3FM, the FF5FM, and the HXZqFM. For instance, the EG premium is 0.44% ($t = 2.15$) per month under FF5FM and 0.47% ($t = 2.26$) per month under XHZqFM. Inspecting the LCAPM estimates, we find that low-EG firms are exposed to significantly higher liquidity risk than are high-EG firms over both earlier and recent subperiods. The LCAPM, once again, captures the EG effect, e.g., the LCAPM-adjusted return difference between the low- and the high-EG portfolio is insignificant at 0.184% ($t = 0.46$) per month over the recent 25 years.

[Table 6 about here]

The above results presnet an interesting question as to why the EG premium appears only in the recent sample period. One possible explanation is the inclusion of relatively small and illiquid NASDAQ stocks during this period. We, thus, test the EG premium separately, based on the NYSE/AMEX/ARCA sample and the NASDAQ sample. Similar to the analysis above, we form decile portfolios using the same NYSE breakpoints for both NYSE/AMEX/ARCA and NASDAQ stocks.

Panel A of Table 7 presents the results over 1974–2014 period (data for NASDAQ stocks become available from 1973). For the NYSE/AMEX/ARCA sample, the EG premium is indeed less significant at 0.245% ($t = 1.85$) per month. All other models considered in this paper are able to explain the EG premium when NASDAQ stocks are excluded. The NASDAQ sample, however, exhibits a strong EG premium. Before any risk adjustment, low-EG firms outperform high-EG firms by 0.432% ($t = 3.15$) per month. After adjusting for the FF5FM and the HXZqFM, we find that the EG premiums remain significant at 0.373% ($t = 2.06$) and 0.419% ($t = 2.06$) per month, respectively. Panel B shows consistent results for NYSE/AMEX/ARCA and NASDAQ stocks over the recent 25-year period (1989–2014). With the NYSE/AMEX/ARCA sample over the recent 25 years, the EG premium is weak at 0.292% ($t = 1.64$) per month before risk adjustment, and it is 0.268% ($t = 1.30$) and 0.248% ($t = 1.14$) after adjusting for the FF5FM and the HXZqFM. With the NASDAQ sample over 1989–2014, the EG premium again is large and significant at 0.580% ($t = 3.28$) per month, which the FF5FM and the HXZqFM fail to explain. If fact, both the FF5FM and the HXZqFM show little evidence that would describe the performance of *EG* decile portfolios (except for the high-*EG* portfolio) when the sample contains the NASDAQ stocks. Consequently, each of the two models yields a large and significant *EG* premium at 0.567% ($t = 2.35$) per month under the FF5FM and 0.610% ($t = 2.38$) per month under the HXZqFM.

In contrast, the LCAPM largely explains the performance of the *EG* decile portfolios within both the NYSE/AMEX/ARCA sample and the NASDAQ sample. Consistent with the full sample case as well as with our liquidity proposition that low-*EG* stocks are exposed to higher liquidity risk than high-*EG* stocks, the loading on the liquidity risk factor of the LCAPM declines from the low- to high-*EG* deciles. After adjusting for the LCAPM, we find that results in both panels of Table 7 indicate that the power of employment growth to predict returns diminishes. With the NASDAQ sample over 1984–2014, for instance, the LCAPM explains the performance of all decile portfolios, and the LCAPM-adjusted return difference between the two extreme *EG* deciles is 0.288% ($t = 0.64$) per month.

[Table 7 about here]

Overall, results in Table 7 show that the inclusion of NASDAQ stocks is a likely reason on why the pre-liquidity-risk-adjusted *EG* premium is significant only in the second half of the sample period. The observed *EG* premium is likely to be a NASDAQ driven premium, which seems to be well explained by liquidity risk.

Further, we conduct two alternative subsample analyses based on industry competition and transparency. Prior studies show that firms with stronger market power are less sensitive to order flows and have higher stock liquidity than those with lower market power (Peress, 2010; Kale and Loon, 2011).

We use Herfindahl-Hirschman Index (HHI) to measure industry concentration. Results are presented in Appendix Table A.1. It show that the EG premium is higher in the low-HHI (i.e., low concentration) subsample than the high-HHI subsample before any risk adjustment. Specifically, the EG premiums are significant at 0.346%, 0.281%, and 0.265% per month in low-, medium-, and high-HHI subsamples, respectively. The LCAPM, however, explains the EG premium for all three HHI subsamples. These results suggest that, after taking into account the industry concentration, liquidity risk still plays a significant role in explaining the EG premium.

Following Morck et al. (2000) and Durnev et al. (2009), we estimate industry transparency as the degree of stock price asynchronicity. If a firm's stock return moves asynchronously with the market and industry returns, more firm-specific information is included in stock prices and the firm is less transparent. Specifically, we run the following regression rolling each five-year for each stock:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,ind} f_{INDMKT,t} + \beta_{i,m} f_{MKT,t} + \varepsilon_{i,t}, \tag{15}$$

where $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the month-t risk-free rate, $f_{INDMKT,t}$ is the month-t value of the two-digit SIC industry value-weighted return, $f_{MKT,t}$ is the month-t value of the market factor. Industry transparency is the two-digit SIC industry median of $ln(\frac{1-R_i^2}{R_i^2})$, where R_i^2 is the R-square from Equation (15).

We report the test results in Appendix Table A.2. It shows that the EG premium is more pronounced in the low-transparency subsamples. It is significant under the FF5FM and HXZqFM in the low-transparency subsample but insignificant under the LCAPM.[21]

[21] In untabulated results, we also measure transparency by estimating firms' discretionary earnings management following Lang et al. (2012). Further, we calculate an alternative industry adjusted EG. Our results are consistent in these tests.

Finally, we perform some further subperiod analyses. First, we use the economic crisis to split the sample. Specifically, we divide the full sample into recessions and other periods.[22] Appendix Table A.3 shows that the *EG* premium presents only in nonrecession periods, while the LCAPM still explains the *EG* premium.[23] Second, we use the decimalization of stock prices to split the sample. Previous studies (e.g., Fang et al., 2009; Bharath et al., 2013; Edmans et al., 2013; Brogaard et al., 2017; Kang and Kim, 2017) use decimalization as an exogenous shock to stock liquidity. Specifically, we divide the full sample into two subperiods: before and after 2001. Appendix Table A.4 reports the results. It shows that the *EG* premium is significant before (1964–2000) but turns insignificant after (2001–2014) the decimalization. The FF3FM, the PS liquidity-extended FF3FM, the FF5FM, and the HXZqFM all have difficulties in capturing the *EG* premium before the decimalization while the LCAPM, again, captures the *EG* premium.

While we find consistent results in our robustness tests, our liquidity risk explanation for the *EG* premium can still be related to some latent effects such as micro-cap and transaction costs. Hou et al. (2020) find that micro-cap firms play an important role in the cross-sectional return predictability. Novy-Marx and Velikov (2016) and Chen and Velikov (2021) show that transaction costs largely reduce the premium generated by firm characteristics. Though it is out of the scope of this study, future research can further explore why liquidity risk has the explanatory power of the *EG* premium.

[22]Recession periods are identified based on the NBER data: http://www.nber.org/cycles.html.

[23]In untabulated results, we also use the consumption-to-wealth ratio (CAY) to identify the business cycles following Lettau and Ludvigson (2001). The results are similar.

4. CONCLUSION

Given the relationship of a firm's employment growth (EG) to its investment opportunities, financial health, and information environment, which are fundamental sources of stock liquidity, we conjecture that liquidity risk has the potential to explain the return predictability of EG as documented by Belo et al. (2014). Our study provides empirical evidence confirming the conjecture: stocks of firms with low EG are less liquid and exposed to high liquidity risk than are stocks of firms with high EG. After adjusting for liquidity risk, we find that the predictive power of EG diminishes. Overall, we provide a liquidity risk explanation to the cross-sectional return predictability of employment growth.

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Table 1
Descriptive statistics

This table reports descriptive statistics and correlations for the following variables:

EG: employment growth rate, as defined in Equation (1);

IK: investment rate, i.e., the ratio of net capital expenditure to fixed assets, as defined in Equation (2);

MV: market capitalization, measured in millions of dollars;

B/M: book-to-market ratio;

OP: book-equity-deflated operating profitability;

AG: total asset growth rate;

ADG: advertising growth rate;

NoInst: number of institutional investors;

InstOwn: institutional ownership, i.e., the proportion of a company's shares owned by institutional investors;

Leverage: market leverage, i.e., the ratio of book debt to the sum of book debt and market cap, as defined in Gomes and Schmid (2010);

WWindex: Whited and Wu (2006) index; a linear combination of cash flow to total assets, sales growth, long-term debt to total assets, log total assets, dividend policy indicator, and the firm's three-digit industry sales growth, as defined in Equation (5);

AQ: accrual quality as defined in Equation (6);

DV: average daily dollar volume over the prior 12 months, where daily dollar volume is the number of shares traded on a day times the closing price on that day;

RV: daily ratio of the absolute return on a day to the dollar volume on that day averaged over the prior 12 months;

LM: standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months;

CS: average of the high-low-price-based monthly bid-ask spread estimates of Corwin and Schultz (2012) over the prior 12 months.

At the end of June each year, we work out the cross-sectional mean and standard deviation for each of the above variables. This table reports the time-series averages of the cross-sectional estimates. Likewise, we compute the Spearman rank correlations of *EG* with other variables at the end of June each year and report the time-series averages of the cross-sectional estimates. The sample includes nonfinancial and nonregulated ordinary common stocks.

	EG(%)	*IK*	*MV*($m)	*B/M*	*OP*	*AG*	*ADG*	*NoInst*	*InstOwn*	*Leverage*	*WWindex*	*AQ*	*DV*($m)	*RV*($\times 10^6$)	*LM*	*CS*(%)
Panel A: NYSE/AMEX/ARCA stocks over 6/1964–6/2013 (50 years)																
Descriptive statistics																
Mean	3.374	0.221	2476.7	0.911	0.285	0.137	0.323	95.969	0.356	0.424	−0.254	0.119	13.37	3.918	8.347	1.255
Stdev	22.95	0.337	9012.0	1.038	2.961	0.498	12.720	146.761	0.288	0.217	1.731	0.149	33.77	19.21	21.57	1.514
Spearman correlation																
EG	1	0.314	0.122	−0.228	0.203	0.559	0.333	0.105	0.079	−0.169	−0.045	−0.063	0.126	−0.129	−0.101	−0.125
Panel B: NASDAQ stocks over 6/1984–6/2013 (30 years)																
Descriptive statistics																
Mean	6.562	0.335	863.4	0.817	−0.028	0.213	0.612	40.631	0.290	0.314	−0.131	0.146	10.55	11.05	20.98	4.437
Stdev	32.67	1.063	6155.6	1.616	14.48	0.935	11.818	74.575	0.262	0.233	1.632	0.170	74.65	59.34	35.14	5.214
Spearman correlation																
EG	1	0.366	0.276	−0.240	0.174	0.541	0.312	0.225	0.170	−0.209	−0.173	−0.068	0.292	−0.293	−0.242	−0.265

Table 2

Characteristics of the EG portfolios

Using NYSE breakpoints, we form equal-weighted employment growth (EG) decile portfolios at the end of June each year. This table reports the characteristics of these portfolios. The notation MV is the market capitalization, B/M is the book-to-market ratio, OP is the book-equity-deflated operating profitability, AG is the total asset growth rate, IK is the investment rate, ADG is the advertising growth rate, *NoInst* is the number of institutional investors, *InstOwn* is the proportion of shares owned by institutional investors, *Leverage* is the market leverage (i.e., the ratio of book debt to the sum of book debt and market capitalization), *WWindex* is the Whited-Wu (2006) index, AQ is the accruals quality, CS is the average of the Corwin and Schultz (2012) bid-ask spread estimates over the 12 months prior to portfolio formation, DV is the average of daily dollar trading volumes over the 12 months prior to portfolio formation, RV is the ratio of the absolute return on a day to the dollar trading volume on the day averaged over the 12 months prior to portfolio formation, and LM is the standardized turnover-adjusted number of zero daily trading volumes over the 12 months prior to portfolio formation.

	Low-EG	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	High-EG	$L-H$
					NYSE/AMEX/ARCA/NASDAQ stocks over 6/1964–6/2013 (50 years)						
EG (%)	−32.91	−8.567	−3.948	−1.220	1.013	3.166	5.782	9.321	15.63	43.66	−76.57
MV ($m)	500.3	1192.8	1735.4	1881.0	2005.2	2291.8	1709.8	1713.0	1270.8	1038.4	−538.2
B/M	1.181	1.117	1.083	0.965	0.927	0.875	0.812	0.761	0.733	0.669	0.512
OP	−0.298	−0.006	0.767	0.208	0.358	0.246	0.269	0.268	0.155	0.111	−0.409
AG	−0.053	0.019	0.043	0.062	0.082	0.101	0.129	0.154	0.225	0.592	−0.645
IK	0.152	0.198	0.200	0.209	0.220	0.237	0.255	0.284	0.330	0.446	−0.294
ADG	0.073	0.104	0.114	0.816	0.449	0.178	0.196	0.433	0.432	1.201	−1.128
NoInst	43.021	65.561	83.732	90.545	98.572	106.040	94.735	89.049	81.573	66.117	−23.096
InstOwn	0.274	0.351	0.389	0.393	0.408	0.421	0.419	0.411	0.403	0.370	−0.096
Leverage	0.441	0.449	0.428	0.413	0.389	0.387	0.367	0.354	0.338	0.331	0.111
WWindex	−0.140	−0.198	−0.205	−0.221	−0.267	−0.249	−0.227	−0.215	−0.200	−0.195	0.055
AQ	0.155	0.125	0.117	0.112	0.109	0.107	0.108	0.110	0.115	0.133	0.022
CS (%)	5.112	3.246	2.712	2.670	2.548	2.121	2.202	2.309	2.485	2.773	2.339
					NYSE/AMEX/ARCA stocks over 6/1964–6/2013 (50 years)						
DV ($\$m$)	7.130	11.17	13.53	14.28	17.09	18.14	14.91	16.46	13.26	11.15	−4.023
RV (10^6)	11.76	4.544	3.496	2.859	2.309	1.996	1.681	2.152	2.391	2.699	9.065
LM	12.92	9.963	8.990	7.495	7.315	6.293	6.604	6.566	7.285	6.545	6.379
					NASDAQ stocks over 6/1984–6/2013 (30 years)						
DV ($\$m$)	2.901	4.960	5.308	5.911	7.304	7.998	10.88	12.54	14.85	20.45	−17.55
RV (10^6)	23.90	16.14	10.84	10.81	13.69	7.768	7.245	5.837	5.564	6.294	17.61
LM	28.59	28.14	26.11	27.92	27.78	22.65	20.24	18.49	14.83	12.02	16.56

Table 3
Firm employment growth and the sources of liquidity: Regression analysis

This table reports the results of regressing firm employment growth rate (EG) on investment opportunities, information environment, and firm financial health. We proxy investment opportunities by investment rate (IK) and asset growth (AG); information environment by advertising growth rate (ADG), number of institutional investors (*NoInst*) and institutional ownership (*InstOwn*); and financial health by book-to-market ratio (logarithm of B/M), leverage (*Leverage*), Whited-Wu (2006) index (*WWindex*), and accruals quality (AQ). The sample includes NYSE/AMEX/ARCA/NASDAQ nonfinancial and nonutility ordinary common stocks over 1964–2014. Numbers in parentheses are t-statistics.

	IK as the measure of investment opportunity											
c	−0.037	−0.051	−0.040	0.014	−0.017	0.005	−0.070	−0.068	−0.050	0.022	−0.019	0.006
	(−5.23)	(−4.97)	(−4.28)	(1.59)	(−1.37)	(0.41)	(−4.59)	(−6.22)	(−4.98)	(1.68)	(−1.86)	(0.72)
IK	0.201	0.167	0.167	0.213	0.182	0.182	0.261	0.186	0.187	0.071	0.020	0.020
	(10.27)	(8.89)	(8.87)	(10.28)	(8.81)	(8.78)	(8.44)	(8.30)	(8.29)	(1.44)	(1.69)	(1.69)
ADG	0.016			0.016			0.017			0.001		
	(5.58)			(5.68)			(1.65)			(1.44)		
ln(*NoInst*)		0.008			0.012			0.012			0.015	
		(5.67)			(7.08)			(6.87)			(7.03)	
InstOwn			0.042			0.052			0.059			0.069
			(5.28)			(5.88)			(6.69)			(5.82)
ln(*B/M*)	−0.040	−0.042	−0.043									
	(−12.66)	(−12.57)	(−13.57)									
Leverage				−0.085	−0.072	−0.076						
				(−8.05)	(−7.41)	(−7.85)						
WWindex							−0.178	−0.081	−0.088			
							(−3.54)	(−5.10)	(−6.13)			
AQ										−0.110	−0.058	−0.064
										(−6.30)	(−4.88)	(−5.28)
	AG as the measure of investment opportunity											
c	−0.015	−0.027	−0.020	0.035	0.013	0.028	−0.017	−0.036	−0.019	0.015	−0.019	0.004
	(−2.79)	(−3.50)	(−2.71)	(5.10)	(1.38)	(3.27)	(−1.35)	(−4.78)	(−2.71)	(2.96)	(−2.03)	(0.57)
AG	0.321	0.197	0.197	0.325	0.204	0.205	0.281	0.219	0.220	0.202	0.057	0.057
	(9.42)	(10.27)	(10.27)	(10.35)	(10.07)	(10.08)	(10.59)	(11.27)	(11.27)	(8.56)	(1.81)	(1.80)
ADG	0.015			0.016			0.013			0.001		
	(1.65)			(2.44)			(1.00)			(1.39)		
ln(*NoInst*)		0.007			0.009			0.012			0.014	
		(6.02)			(6.85)			(8.10)			(6.83)	
InstOwn			0.041			0.046			0.059			0.067
			(6.26)			(6.84)			(8.97)			(5.83)
ln(*B/M*)	−0.029	−0.033	−0.034									
	(−8.19)	(−14.36)	(−15.05)									
Leverage				−0.093	−0.084	−0.085						
				(−9.65)	(−8.98)	(−9.19)						
WWindex							−0.085	−0.023	−0.030			
							(−2.03)	(−2.18)	(−3.30)			
AQ										−0.110	−0.064	−0.070
										(−6.78)	(−5.00)	(−5.43)

Table 4

Performance of decile portfolios sorted by employment growth

Using NYSE breakpoints, we form equal- and value-weighted EG decile portfolios at the end of June each year and hold them for the subsequent 12 months. Following Fama and French (2008), we define stocks below the 20% of market capitalization of NYSE stocks as micro-cap stocks. The row labelled Raw shows the raw mean returns measured on a monthly basis. The symbol $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{LF,t}$ is the month-t value of the Liu (2006) liquidity factor, $f_{SMB,t}$ is the month-t value of the Fama–French size factor, $f_{HML,t}$ is the month-t value of the Fama–French book-to-market factor, $f_{RMW,t}$ is the month-t value of the Fama–French profitability factor, $f_{CMA,t}$ is the month-t value of the Fama–French investment factor, $f_{WML,t}$ is the month-t value of the momentum factor, $f_{PSF,t}$ is the month-t value of the Pastor and Stambaugh (2003) traded liquidity factor, $f_{ME,t}$ is the month-t value of the HXZ (i.e., Hou et al., 2015) size factor, $f_{ROA,t}$ is the month-t value of the HXZ profitability factor, and $f_{I/A,t}$ is the month-t value of the HXZ investment factor. The sample includes NYSE/AMEX/ARCA/NASDAQ nonfinancial and nonregulated stocks with daily trading volumes available in the 12 months prior to portfolio formation. The testing period is 7/1964–6/2014 (600 months). However, when using the Pastor and Stambaugh (2003) traded liquidity factor, the testing period is 7/1968–6/2014 (552 months), and it is 7/1967–6/2014 (564 months) when estimating the HXZ four-factor model. Numbers in parentheses are t-statistics.

	Low-EG	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	High-EG	$L-H$
Panel A: Equal-weighted portfolio returns											
Raw (%)	1.220	1.332	1.254	1.273	1.208	1.283	1.219	1.187	1.170	0.858	0.363
	(4.33)	(5.56)	(5.31)	(5.77)	(5.70)	(5.82)	(5.38)	(4.96)	(4.58)	(3.09)	(3.48)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	−0.079	0.114	0.025	0.096	0.076	0.119	0.075	0.049	0.021	−0.325	0.245
	(−0.74)	(1.51)	(0.38)	(1.27)	(1.25)	(2.11)	(1.41)	(0.84)	(0.36)	(−4.67)	(1.91)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,w}f_{WML,t}+\varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	−0.050	0.125	0.034	0.139	0.101	0.142	0.099	0.049	0.037	−0.259	0.209
	(−0.46)	(1.62)	(0.50)	(1.82)	(1.63)	(2.46)	(1.83)	(0.81)	(0.63)	(−3.71)	(1.60)
$\hat{\beta}_{i,w}$	−0.033	−0.013	−0.010	−0.049	−0.028	−0.026	−0.027	0.000	−0.018	−0.074	0.041
	(−1.29)	(−0.72)	(−0.62)	(−2.76)	(−1.98)	(−1.94)	(−2.18)	(0.03)	(−1.33)	(−4.58)	(1.37)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,p}f_{PSF,t}+\varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	−0.075	0.095	0.075	0.115	0.069	0.128	0.078	0.043	0.003	−0.350	0.275
	(−0.65)	(1.17)	(1.11)	(1.44)	(1.12)	(2.13)	(1.43)	(0.72)	(0.06)	(−4.74)	(2.00)
$\hat{\beta}_{i,p}$	0.025	0.018	0.027	0.044	0.043	0.028	0.031	0.050	0.043	0.035	−0.009
	(0.79)	(0.78)	(1.45)	(2.00)	(2.51)	(1.70)	(2.06)	(3.06)	(2.55)	(1.71)	(−0.25)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,r}f_{RMW,t}+\beta_{i,c}f_{CMA,t}+\varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	0.045	0.148	0.012	0.055	0.023	0.116	0.080	0.082	0.081	−0.187	0.232
	(0.44)	(2.01)	(0.19)	(0.72)	(0.39)	(2.03)	(1.49)	(1.38)	(1.42)	(−2.82)	(1.90)
$\hat{\beta}_{i,r}$	−0.475	−0.211	−0.122	0.008	0.030	−0.026	−0.033	−0.120	−0.125	−0.261	−0.214
	(−9.40)	(−5.78)	(−3.80)	(0.21)	(0.99)	(−0.91)	(−1.24)	(−4.12)	(−4.42)	(−7.99)	(−3.56)
$\hat{\beta}_{i,c}$	0.312	0.273	0.352	0.242	0.263	0.121	0.095	0.122	−0.004	−0.157	0.469
	(4.32)	(5.23)	(7.66)	(4.56)	(6.19)	(3.01)	(2.51)	(2.93)	(−0.09)	(−3.37)	(5.45)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{ME,t}+\beta_{i,r}f_{ROA,t}+\beta_{i,c}f_{I/A,t}+\varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	0.180	0.250	0.128	0.169	0.082	0.171	0.157	0.145	0.162	−0.090	0.269
	(1.55)	(3.01)	(1.82)	(1.99)	(1.27)	(2.72)	(2.67)	(2.29)	(2.53)	(−1.18)	(1.94)
$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,l}f_{LF,t}+\varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	−0.128	0.114	0.059	0.125	0.138	0.177	0.133	0.092	0.060	−0.257	0.129
	(−0.68)	(0.82)	(0.46)	(1.08)	(1.32)	(1.65)	(1.20)	(0.72)	(0.44)	(−1.71)	(0.53)
$\hat{\beta}_{i,m}$	1.388	1.250	1.243	1.173	1.114	1.169	1.176	1.205	1.263	1.337	0.051
	(26.3)	(32.1)	(34.2)	(36.0)	(38.0)	(38.9)	(37.6)	(33.7)	(32.6)	(31.7)	(0.75)
$\hat{\beta}_{i,l}$	0.454	0.344	0.308	0.284	0.197	0.213	0.171	0.164	0.138	0.082	0.373
	(6.49)	(6.66)	(6.39)	(6.59)	(5.07)	(5.35)	(4.14)	(3.45)	(2.70)	(1.46)	(4.16)

[Cont.]

Table 4 (Continued)

	Panel B: Equal-weighted portfolio returns with all-but-micro samples										
Raw (%)	1.191	1.254	1.218	1.199	1.275	1.115	1.231	1.114	1.035	0.840	0.350
	(4.65)	(5.38)	(5.51)	(5.58)	(5.64)	(4.83)	(5.09)	(4.33)	(3.78)	(2.67)	(2.56)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	−0.062	0.029	0.053	0.064	0.133	0.002	0.161	0.036	−0.051	−0.278	0.216
	(−0.84)	(0.45)	(0.82)	(1.07)	(2.25)	(0.03)	(2.69)	(0.57)	(−0.74)	(−3.19)	(1.89)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	−0.012	0.065	0.097	0.084	0.168	0.014	0.172	0.062	−0.010	−0.195	0.183
	(−0.17)	(0.98)	(1.47)	(1.39)	(2.79)	(0.24)	(2.81)	(0.96)	(−0.14)	(−2.24)	(1.59)
$\hat{\beta}_{i,w}$	−0.055	−0.039	−0.049	−0.023	−0.038	−0.014	−0.012	−0.029	−0.045	−0.092	0.037
	(−3.27)	(−2.64)	(−3.26)	(−1.66)	(−2.82)	(−1.05)	(−0.83)	(−1.97)	(−2.85)	(−4.64)	(1.41)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,p} f_{PSF,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	−0.052	0.021	0.052	0.058	0.151	0.009	0.173	0.049	−0.025	−0.275	0.224
	(−0.68)	(0.32)	(0.77)	(0.96)	(2.49)	(0.15)	(2.90)	(0.76)	(−0.36)	(−3.06)	(1.90)
$\hat{\beta}_{i,p}$	0.008	0.021	0.039	0.043	−0.000	0.058	0.058	0.048	0.021	0.003	0.005
	(0.37)	(1.13)	(2.10)	(2.57)	(−0.03)	(3.82)	(3.58)	(2.76)	(1.12)	(0.11)	(0.15)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	−0.107	−0.054	−0.077	−0.053	0.066	−0.036	0.171	0.085	0.019	−0.079	−0.028
	(−1.56)	(−0.84)	(−1.25)	(−0.95)	(1.14)	(−0.66)	(2.80)	(1.35)	(0.28)	(−0.95)	(−0.26)
$\hat{\beta}_{i,r}$	−0.094	0.081	0.195	0.193	0.123	0.078	−0.011	−0.017	−0.067	−0.292	0.198
	(−2.83)	(2.64)	(6.51)	(7.08)	(4.37)	(2.90)	(−0.39)	(−0.57)	(−2.04)	(−7.27)	(3.79)
$\hat{\beta}_{i,c}$	0.399	0.272	0.295	0.239	0.131	0.084	0.021	−0.149	−0.157	−0.366	0.765
	(8.35)	(6.15)	(6.86)	(6.10)	(3.24)	(2.17)	(0.51)	(−3.41)	(−3.32)	(−6.36)	(10.23)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{ME,t} + \beta_{i,r} f_{ROA,t} + \beta_{i,c} f_{I/A,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	−0.054	−0.005	−0.016	−0.020	0.105	0.009	0.211	0.154	0.071	−0.000	−0.054
	(−0.73)	(−0.06)	(−0.22)	(−0.31)	(1.65)	(0.15)	(3.36)	(2.30)	(0.95)	(−0.00)	(−0.45)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.160	0.270	0.229	0.239	0.310	0.161	0.299	0.197	0.143	−0.067	0.227
	(1.38)	(2.74)	(2.50)	(2.78)	(3.50)	(1.77)	(2.93)	(1.82)	(1.18)	(−0.45)	(1.21)
$\hat{\beta}_{i,m}$	1.195	1.103	1.069	1.037	1.079	1.086	1.098	1.139	1.167	1.293	−0.098
	(37.50)	(40.53)	(42.36)	(43.81)	(44.27)	(43.34)	(39.07)	(38.15)	(34.87)	(31.96)	(−1.91)
$\hat{\beta}_{i,l}$	−0.015	−0.013	0.027	0.006	−0.023	−0.050	−0.100	−0.163	−0.232	−0.322	0.307
	(−0.35)	(−0.36)	(0.80)	(0.18)	(−0.73)	(−1.52)	(−2.70)	(−4.13)	(−5.25)	(−6.02)	(4.51)

[Cont.]

Table 4 (Continued)

	Panel C: Value-weighted portfolio returns										
Raw (%)	1.084	1.016	0.952	1.034	0.957	0.906	0.947	0.947	1.117	0.819	0.264
	(4.92)	(5.03)	(5.00)	(5.88)	(5.41)	(4.83)	(4.82)	(4.47)	(4.75)	(3.16)	(1.81)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.014	0.034	−0.001	0.126	0.116	0.022	0.075	0.131	0.239	−0.045	0.059
	(0.16)	(0.42)	(−0.01)	(1.62)	(1.67)	(0.33)	(1.02)	(1.73)	(3.02)	(−0.57)	(0.50)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	−0.015	0.012	−0.016	0.093	0.095	0.049	0.113	0.109	0.215	−0.019	0.003
	(−0.17)	(0.15)	(−0.20)	(1.17)	(1.34)	(0.72)	(1.52)	(1.41)	(2.67)	(−0.23)	(0.03)
$\hat{\beta}_{i,w}$	0.033	0.025	0.017	0.038	0.024	−0.030	−0.044	0.025	0.026	−0.030	0.063
	(1.58)	(1.29)	(0.88)	(2.07)	(1.45)	(−1.92)	(−2.55)	(1.40)	(1.43)	(−1.62)	(2.26)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,p} f_{PSF,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	−0.002	0.067	0.021	0.134	0.141	0.024	0.076	0.080	0.230	−0.086	0.084
	(−0.03)	(0.75)	(0.24)	(1.60)	(1.92)	(0.35)	(0.98)	(1.00)	(2.80)	(−1.05)	(0.67)
$\hat{\beta}_{i,p}$	−0.023	−0.051	0.024	−0.013	0.007	0.002	0.001	0.036	0.076	0.007	−0.030
	(−0.89)	(−2.08)	(1.05)	(−0.57)	(0.36)	(0.13)	(0.07)	(1.67)	(3.34)	(0.31)	(−0.87)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	−0.090	−0.040	−0.165	−0.056	−0.051	−0.020	−0.026	0.153	0.305	0.089	−0.179
	(−1.06)	(−0.51)	(−2.10)	(−0.76)	(−0.77)	(−0.30)	(−0.37)	(2.08)	(3.78)	(1.15)	(−1.56)
$\hat{\beta}_{i,r}$	−0.006	−0.070	0.183	0.180	0.227	0.184	0.311	0.142	−0.046	−0.107	0.101
	(−0.14)	(−1.80)	(4.71)	(4.98)	(6.91)	(5.63)	(8.93)	(3.91)	(−1.15)	(−2.79)	(1.77)
$\hat{\beta}_{i,c}$	0.529	0.483	0.475	0.577	0.424	−0.123	−0.049	−0.344	−0.225	−0.451	0.981
	(8.81)	(8.66)	(8.56)	(11.18)	(9.01)	(−2.64)	(−0.99)	(−6.64)	(−3.95)	(−8.27)	(12.09)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{ME,t} + \beta_{i,r} f_{ROA,t} + \beta_{i,c} f_{I/A,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	−0.141	−0.068	−0.093	−0.064	−0.076	0.029	0.006	0.168	0.339	0.156	−0.297
	(−1.50)	(−0.78)	(−1.06)	(−0.77)	(−1.02)	(0.40)	(0.08)	(2.11)	(3.74)	(1.80)	(−2.32)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.069	0.138	−0.005	0.135	0.063	0.035	0.092	0.110	0.259	−0.029	0.098
	(0.72)	(1.59)	(−0.06)	(1.62)	(0.86)	(0.50)	(1.20)	(1.32)	(2.75)	(−0.27)	(0.68)
$\hat{\beta}_{i,m}$	1.133	0.988	0.987	0.896	0.914	0.950	0.966	1.007	1.098	1.169	−0.035
	(41.97)	(40.54)	(40.55)	(38.30)	(44.42)	(48.21)	(45.19)	(43.12)	(41.54)	(38.95)	(−0.88)
$\hat{\beta}_{i,l}$	0.082	−0.036	0.107	0.081	0.058	−0.014	−0.056	−0.125	−0.167	−0.245	0.327
	(2.29)	(−1.11)	(3.32)	(2.62)	(2.12)	(−0.53)	(−1.98)	(−4.03)	(−4.76)	(−6.17)	(6.12)

Table 5

Performance of the employment growth portfolios: Subsample analysis

Using NYSE breakpoints, we divide the sample of NYSE/AMEX/ARCA/NASDAQ nonfinancial and nonutility stocks into three IK-based subsamples at the end of June each year starting from 1964. At the end of June each year, stocks in each of the three IK subsamples are sorted into equal-weighted quintile portfolios based on NYSE EG breakpoints. We hold the quintile portfolios for the subsequent 12 months. The row labelled Raw shows the raw mean returns measured on a monthly basis. The symbol $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{SMB,t}$ is the month-t value of the Fama–French size factor, $f_{HML,t}$ is the month-t value of the Fama–French book-to-market factor, $f_{RMW,t}$ is the month-t value of the Fama–French profitability factor, $f_{CMA,t}$ is the month-t value of the Fama–French investment factor, $f_{ME,t}$ is the month-t value of the HXZ (i.e., Hou et al., 2015) size factor, $f_{ROA,t}$ is the month-t value of the HXZ profitability factor, $f_{I/A,t}$ is the month-t value of the HXZ investment factor, and $f_{LF,t}$ is the month-t value of the Liu (2006) liquidity factor. The testing period is 7/1964–6/2014 (600 months) except for the HXZ q-factor model, which is estimated from 7/1967–6/2014 (564 months). Numbers in parentheses are t-statistics.

	Low-EG	$Q2$	$Q3$	$Q4$	High-EG	$L-H$
Panel A: Results of the low-IK subsample						
Raw (%)	1.292	1.316	1.402	1.296	1.098	0.194
	(4.96)	(5.86)	(6.37)	(5.56)	(4.29)	(2.09)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,r}f_{RMW,t}+\beta_{i,c}f_{CMA,t}+\varepsilon_{i,t}$					
$\hat{\alpha}_i$ (%)	0.099	0.046	0.184	0.107	−0.092	0.191
	(1.00)	(0.59)	(2.30)	(1.32)	(−1.06)	(1.45)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{ME,t}+\beta_{i,h}f_{ROA,t}+\beta_{i,r}f_{I/A,t}+\varepsilon_{i,t}$					
$\hat{\alpha}_i$ (%)	0.203	0.133	0.257	0.187	−0.052	0.254
	(1.82)	(1.50)	(2.88)	(2.08)	(−0.54)	(1.73)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,l}f_{LF,t}+\varepsilon_{i,t}$					
$\hat{\alpha}_i$ (%)	−0.029	0.104	0.199	0.126	−0.107	0.077
	(−0.17)	(0.81)	(1.59)	(0.93)	(−0.70)	(0.34)
$\hat{\beta}_{i,m}$	1.313	1.198	1.178	1.198	1.282	0.030
	(27.2)	(33.2)	(33.4)	(31.5)	(29.8)	(0.47)
$\hat{\beta}_{i,l}$	0.472	0.378	0.379	0.304	0.290	0.181
	(7.37)	(7.91)	(8.11)	(6.02)	(5.10)	(2.12)
Panel B: Results of the medium-IK subsample						
Raw (%)	1.286	1.273	1.221	1.232	1.173	0.113
	(5.23)	(5.94)	(6.00)	(5.59)	(4.81)	(1.18)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{SMB,t}+\beta_{i,h}f_{HML,t}+\beta_{i,r}f_{RMW,t}+\beta_{i,c}f_{CMA,t}+\varepsilon_{i,t}$					
$\hat{\alpha}_i$ (%)	0.102	0.025	0.029	0.094	−0.034	0.136
	(1.24)	(0.41)	(0.53)	(1.57)	(−0.50)	(1.28)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,s}f_{ME,t}+\beta_{i,h}f_{ROA,t}+\beta_{i,r}f_{I/A,t}+\varepsilon_{i,t}$					
$\hat{\alpha}_i$ (%)	0.222	0.111	0.105	0.122	−0.015	0.238
	(2.40)	(1.61)	(1.68)	(1.90)	(−0.20)	(1.99)
	$R_{i,t}-R_{f,t}=\alpha_i+\beta_{i,m}f_{MKT,t}+\beta_{i,l}f_{LF,t}+\varepsilon_{i,t}$					
$\hat{\alpha}_i$ (%)	0.055	0.164	0.169	0.155	−0.001	0.056
	(0.36)	(1.52)	(1.80)	(1.39)	(−0.01)	(0.28)
$\hat{\beta}_{i,m}$	1.253	1.141	1.087	1.142	1.260	−0.007
	(29.4)	(37.7)	(41.2)	(36.4)	(34.1)	(−0.13)
$\hat{\beta}_{i,l}$	0.363	0.245	0.188	0.185	0.256	0.108
	(6.44)	(6.11)	(5.37)	(4.45)	(5.22)	(1.44)

[Cont.]

Table 5 (Continued)

	Low-EG	$Q2$	$Q3$	$Q4$	High-EG	$L-H$
Panel C: Results of the high-IK subsample						
Raw (%)	1.212	1.269	1.082	1.214	0.926	0.285
	(4.36)	(5.20)	(4.73)	(4.99)	(3.32)	(2.92)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$					
$\hat{\alpha}_i$ (%)	0.137	0.151	-0.033	0.136	-0.069	0.206
	(1.33)	(1.76)	(-0.47)	(2.31)	(-1.10)	(1.70)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{ME,t} + \beta_{i,h} f_{ROA,t} + \beta_{i,r} f_{I/A,t} + \varepsilon_{i,t}$					
$\hat{\alpha}_i$ (%)	0.267	0.302	0.078	0.214	0.033	0.234
	(2.28)	(3.27)	(1.05)	(3.29)	(0.42)	(1.67)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}$					
$\hat{\alpha}_i$ (%)	-0.033	0.104	-0.012	0.119	-0.155	0.122
	(-0.18)	(0.72)	(-0.10)	(0.93)	(-1.01)	(0.51)
$\hat{\beta}_{i,m}$	1.334	1.231	1.174	1.220	1.317	0.017
	(26.0)	(30.6)	(35.0)	(33.8)	(30.4)	(0.26)
$\hat{\beta}_{i,l}$	0.317	0.266	0.187	0.149	0.042	0.276
	(4.68)	(4.98)	(4.20)	(3.11)	(0.72)	(3.10)

Table 6
Performance of the employment growth portfolios: subperiod analysis

Using NYSE breakpoints, we form equal-weighted EG decile portfolios at the end of June each year and hold them for the subsequent 12 months. The row labelled Raw shows the raw mean returns measured on a monthly basis. The symbol $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{SMB,t}$ is the month-t value of the Fama–French size factor, $f_{HML,t}$ is the month-t value of the Fama–French book-to-market factor, $f_{RMW,t}$ is the month-t value of the Fama–French profitability factor, $f_{CMA,t}$ is the month-t value of the Fama–French investment factor, $f_{WML,t}$ is the month-t value of the momentum factor, $f_{PSF,t}$ is the month-t value of the Pastor and Stambaugh (2003) traded liquidity factor, $f_{ME,t}$ is the month-t value of the HXZ (i.e., Hou et al., 2015) size factor, $f_{ROA,t}$ is the month-t value of the HXZ profitability factor, $f_{I/A,t}$ is the month-t value of the HXZ investment factor, and $f_{LF,t}$ is the month-t value of the Liu (2006) liquidity factor. The sample includes NYSE/AMEX/ARCA/NASDAQ nonfinancial and nonregulated ordinary common stocks with daily trading volume data available in the 12 months prior to portfolio formation. Numbers in parentheses are t-statistics.

	Low-EG	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	$High$-EG	$L-H$
Panel A: Results over 7/1964–6/1989 (300 months)											
Raw (%)	1.214	1.389	1.189	1.260	1.247	1.281	1.285	1.137	1.146	0.992	0.222
	(3.15)	(4.04)	(3.49)	(3.86)	(3.97)	(3.93)	(3.86)	(3.28)	(3.07)	(2.46)	(1.63)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	−0.328	0.015	−0.191	−0.031	0.027	0.023	0.031	−0.113	−0.139	−0.319	−0.009
	(−3.04)	(0.18)	(−2.24)	(−0.31)	(0.33)	(0.33)	(0.48)	(−1.53)	(−1.76)	(−3.80)	(−0.06)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	−0.294	0.030	−0.188	−0.070	−0.003	0.002	−0.024	−0.134	−0.128	−0.242	−0.052
	(−2.72)	(0.36)	(−2.23)	(−0.67)	(−0.03)	(0.03)	(−0.35)	(−1.78)	(−1.61)	(−2.94)	(−0.38)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	−0.340	−0.029	−0.147	0.015	0.074	0.046	0.045	−0.095	−0.094	−0.302	−0.038
	(−3.04)	(−0.33)	(−1.67)	(0.14)	(0.87)	(0.64)	(0.65)	(−1.24)	(−1.15)	(−3.48)	(−0.27)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	−0.245	0.102	−0.084	0.051	0.121	0.131	0.135	0.015	−0.040	−0.185	−0.060
	(−1.15)	(0.63)	(−0.55)	(0.35)	(0.95)	(1.05)	(1.03)	(0.10)	(−0.24)	(−1.00)	(−0.21)
$\hat{\beta}_{i,m}$	1.416	1.290	1.289	1.223	1.169	1.225	1.238	1.249	1.345	1.425	−0.009
	(26.7)	(31.7)	(34.0)	(33.7)	(36.7)	(39.4)	(37.7)	(33.2)	(31.9)	(30.9)	(−0.13)
$\hat{\beta}_{i,l}$	0.717	0.489	0.463	0.391	0.277	0.285	0.276	0.220	0.273	0.207	0.510
	(8.15)	(7.26)	(7.37)	(6.51)	(5.26)	(5.54)	(5.08)	(3.53)	(3.90)	(2.71)	(4.38)

[Cont.]

Table 6 (Continued)

	Low-EG	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	High-EG	$L-H$
Panel B: Results over 7/1989–6/2014 (300 months)											
Raw (%)	1.227	1.275	1.319	1.285	1.168	1.286	1.153	1.238	1.194	0.723	0.503
	(2.98)	(3.81)	(4.03)	(4.33)	(4.10)	(4.32)	(3.74)	(3.74)	(3.42)	(1.90)	(3.20)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.124	0.224	0.252	0.257	0.168	0.259	0.142	0.230	0.185	−0.331	0.456
	(0.68)	(1.80)	(2.52)	(2.35)	(1.96)	(3.07)	(1.75)	(2.59)	(2.23)	(−2.98)	(2.12)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.345	0.324	0.244	0.246	0.134	0.302	0.179	0.302	0.284	−0.095	0.440
	(1.96)	(2.62)	(2.42)	(2.21)	(1.54)	(3.52)	(2.15)	(3.44)	(3.46)	(−0.92)	(2.15)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.175	0.272	0.254	0.312	0.197	0.298	0.184	0.230	0.196	−0.230	0.404
	(0.94)	(2.16)	(2.50)	(2.85)	(2.26)	(3.51)	(2.27)	(2.55)	(2.33)	(−2.12)	(1.87)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,p} f_{PSF,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.108	0.194	0.224	0.214	0.129	0.235	0.131	0.201	0.163	−0.364	0.472
	(0.58)	(1.55)	(2.24)	(1.98)	(1.52)	(2.78)	(1.60)	(2.27)	(1.96)	(−3.27)	(2.18)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{ME,t} + \beta_{i,r} f_{ROA,t} + \beta_{i,c} f_{I/A,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.497	0.455	0.352	0.343	0.215	0.344	0.286	0.385	0.395	0.027	0.470
	(2.81)	(3.71)	(3.46)	(3.01)	(2.38)	(3.91)	(3.55)	(4.40)	(4.67)	(0.25)	(2.26)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	−0.068	0.127	0.215	0.233	0.204	0.279	0.182	0.214	0.233	−0.252	0.184
	(−0.21)	(0.55)	(1.01)	(1.26)	(1.21)	(1.57)	(1.00)	(1.02)	(1.05)	(−1.05)	(0.46)
$\hat{\beta}_{i,m}$	1.359	1.190	1.166	1.088	1.019	1.071	1.070	1.126	1.118	1.187	0.172
	(13.3)	(16.0)	(16.9)	(18.2)	(18.6)	(18.5)	(18.1)	(16.5)	(15.6)	(15.2)	(1.34)
$\hat{\beta}_{i,l}$	0.308	0.238	0.185	0.182	0.101	0.120	0.057	0.089	−0.014	−0.067	0.375
	(2.70)	(2.87)	(2.40)	(2.72)	(1.66)	(1.86)	(0.87)	(1.17)	(−0.17)	(−0.77)	(2.62)

Table 7

Performance of the EG portfolios: NYSE/AMEX/ARCA sample and NASDAQ sample

Using NYSE breakpoints, we form equal-weighted EG decile portfolios at the end of June each year and hold them for the subsequent 12 months. The row labelled Raw shows the raw mean returns measured on a monthly basis. The symbol $R_{i,t}$ is the month-t return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{SMB,t}$ is the month-t value of the Fama–French size factor, $f_{HML,t}$ is the month-t value of the Fama–French book-to-market factor, $f_{RMW,t}$ is the month-t value of the Fama–French profitability factor, $f_{CMA,t}$ is the month-t value of the Fama–French investment factor, $f_{ME,t}$ is the month-t value of the HXZ (i.e., Hou et al., 2015) size factor, $f_{ROA,t}$ is the month-t value of the HXZ profitability factor, $f_{I/A,t}$ is the month-t value of the HXZ investment factor, and $f_{LF,t}$ is the month-t value of the Liu (2006) liquidity factor. The NYSE/AMEX/ARCA sample and the NASDAQ sample exclude financial and regulated stocks. Numbers in parentheses are t-statistics.

	Low-EG	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	High-EG	$L-H$
Panel A: Results over 7/1974–6/2014 (480 months)											
NYSE/AMEX/ARCA sample											
Raw (%)	1.218	1.352	1.372	1.388	1.328	1.440	1.352	1.303	1.238	0.973	0.245
	(4.06)	(5.13)	(5.44)	(5.82)	(5.74)	(5.99)	(5.67)	(5.32)	(4.78)	(3.45)	(1.85)
$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	−0.358	−0.192	−0.213	−0.118	−0.123	0.041	−0.061	−0.119	−0.166	−0.491	0.133
	(−3.07)	(−2.23)	(−2.64)	(−1.48)	(−1.70)	(0.58)	(−0.90)	(−1.66)	(−2.01)	(−5.39)	(0.90)
$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{ME,t} + \beta_{i,r} f_{ROA,t} + \beta_{i,c} f_{I/A,t} + \varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	−0.244	−0.050	−0.109	−0.024	−0.056	0.083	−0.007	−0.047	−0.072	−0.404	0.160
	(−1.95)	(−0.52)	(−1.09)	(−0.25)	(−0.66)	(1.02)	(−0.09)	(−0.56)	(−0.75)	(−4.00)	(1.00)
$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	−0.285	0.019	0.079	0.160	0.169	0.236	0.180	0.110	0.037	−0.259	−0.026
	(−1.47)	(0.13)	(0.58)	(1.27)	(1.48)	(2.04)	(1.58)	(0.93)	(0.29)	(−1.77)	(−0.11)
$\hat{\beta}_{i,m}$	1.347	1.204	1.168	1.101	1.055	1.108	1.085	1.113	1.151	1.220	0.126
	(25.1)	(28.7)	(30.9)	(31.5)	(33.4)	(34.4)	(34.4)	(34.0)	(32.4)	(30.1)	(1.88)
$\hat{\beta}_{i,l}$	0.464	0.311	0.278	0.235	0.159	0.180	0.146	0.152	0.122	0.100	0.363
	(6.69)	(5.74)	(5.71)	(5.20)	(3.89)	(4.34)	(3.58)	(3.60)	(2.67)	(1.91)	(4.18)
NASDAQ sample											
Raw (%)	1.369	1.523	1.564	1.491	1.372	1.488	1.418	1.467	1.420	0.937	0.432
	(4.18)	(5.52)	(5.51)	(5.74)	(5.29)	(5.71)	(5.09)	(5.18)	(4.75)	(2.91)	(3.15)
$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	0.282	0.456	0.419	0.358	0.193	0.296	0.257	0.321	0.303	−0.090	0.373
	(1.82)	(3.82)	(3.52)	(3.08)	(1.82)	(3.11)	(2.71)	(3.29)	(3.70)	(−0.97)	(2.06)
$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{ME,t} + \beta_{i,r} f_{ROA,t} + \beta_{i,c} f_{I/A,t} + \varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	0.428	0.573	0.470	0.486	0.319	0.351	0.337	0.381	0.384	0.010	0.419
	(2.54)	(4.39)	(3.57)	(4.14)	(2.84)	(3.49)	(3.25)	(3.52)	(3.94)	(0.09)	(2.06)
$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}$											
$\hat{\alpha}_i$ (%)	−0.111	0.239	0.254	0.194	0.069	0.219	0.130	0.170	0.143	−0.329	0.218
	(−0.45)	(1.21)	(1.28)	(1.12)	(0.40)	(1.35)	(0.72)	(0.95)	(0.77)	(−1.66)	(0.69)
$\hat{\beta}_{i,m}$	1.313	1.122	1.169	1.124	1.124	1.134	1.176	1.206	1.232	1.287	0.026
	(19.2)	(20.5)	(21.2)	(23.4)	(23.3)	(25.1)	(23.5)	(24.4)	(23.8)	(23.3)	(0.29)
$\hat{\beta}_{i,l}$	0.460	0.315	0.310	0.339	0.349	0.272	0.257	0.241	0.169	0.083	0.377
	(5.21)	(4.47)	(4.37)	(5.46)	(5.59)	(4.68)	(3.98)	(3.79)	(2.53)	(1.17)	(3.32)

[Cont.]

Table 7 (Continued)

	Low-EG	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	High-EG	$L-H$
Panel B: Results over 7/1989–6/2014 (300 months)											
NYSE/AMEX/ARCA sample											
Raw (%)	0.962	1.106	1.116	1.150	1.088	1.275	1.099	1.071	1.021	0.669	0.292
	(2.58)	(3.48)	(3.78)	(4.04)	(4.02)	(4.50)	(3.96)	(3.81)	(3.45)	(2.06)	(1.64)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	−0.225	−0.117	−0.175	−0.096	−0.125	0.154	−0.045	−0.091	−0.112	−0.494	0.268
	(−1.38)	(−0.98)	(−1.59)	(−0.83)	(−1.28)	(1.52)	(−0.49)	(−0.92)	(−1.01)	(−3.91)	(1.30)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{ME,t} + \beta_{i,r} f_{ROA,t} + \beta_{i,c} f_{I/A,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	−0.177	0.012	−0.096	−0.028	−0.074	0.143	0.011	−0.044	−0.052	−0.425	0.248
	(−1.04)	(0.10)	(−0.72)	(−0.21)	(−0.64)	(1.28)	(0.10)	(−0.39)	(−0.42)	(−3.13)	(1.14)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	−0.253	0.066	0.154	0.214	0.222	0.374	0.242	0.199	0.193	−0.159	−0.094
	(−0.95)	(0.32)	(0.84)	(1.22)	(1.44)	(2.36)	(1.61)	(1.29)	(1.21)	(−0.83)	(−0.29)
$\hat{\beta}_{i,m}$	1.281	1.107	1.028	0.990	0.934	0.985	0.950	0.966	0.967	1.002	0.278
	(14.8)	(16.5)	(17.4)	(17.3)	(18.6)	(19.1)	(19.4)	(19.3)	(18.7)	(16.2)	(2.62)
$\hat{\beta}_{i,l}$	0.255	0.138	0.088	0.084	0.023	0.027	−0.011	−0.002	−0.082	−0.121	0.376
	(2.65)	(1.85)	(1.33)	(1.32)	(0.41)	(0.47)	(−0.20)	(−0.04)	(−1.42)	(−1.75)	(3.17)
NASDAQ sample											
Raw (%)	1.329	1.416	1.506	1.323	1.256	1.285	1.218	1.289	1.227	0.749	0.580
	(3.03)	(3.88)	(3.99)	(3.95)	(3.80)	(3.88)	(3.43)	(3.55)	(3.23)	(1.82)	(3.28)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.596	0.642	0.619	0.444	0.379	0.410	0.409	0.413	0.421	0.029	0.567
	(2.83)	(4.01)	(3.97)	(2.80)	(2.88)	(3.36)	(3.22)	(3.62)	(3.98)	(0.24)	(2.35)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{ME,t} + \beta_{i,r} f_{ROA,t} + \beta_{i,c} f_{I/A,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.782	0.782	0.725	0.568	0.501	0.472	0.513	0.498	0.532	0.172	0.610
	(3.58)	(4.76)	(4.47)	(3.71)	(3.76)	(3.93)	(4.05)	(4.15)	(4.62)	(1.29)	(2.38)
	$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,l} f_{LF,t} + \varepsilon_{i,t}$										
$\hat{\alpha}_i$ (%)	0.014	0.222	0.306	0.174	0.177	0.194	0.164	0.176	0.210	−0.274	0.288
	(0.04)	(0.80)	(1.08)	(0.73)	(0.73)	(0.86)	(0.64)	(0.71)	(0.80)	(−0.99)	(0.64)
$\hat{\beta}_{i,m}$	1.373	1.223	1.251	1.172	1.108	1.148	1.142	1.221	1.178	1.249	0.125
	(11.9)	(13.6)	(13.5)	(15.1)	(14.1)	(15.7)	(13.7)	(15.3)	(13.8)	(13.9)	(0.85)
$\hat{\beta}_{i,l}$	0.330	0.283	0.263	0.260	0.208	0.184	0.125	0.141	0.019	−0.050	0.380
	(2.56)	(2.83)	(2.55)	(3.01)	(2.37)	(2.26)	(1.35)	(1.59)	(0.20)	(−0.50)	(2.33)

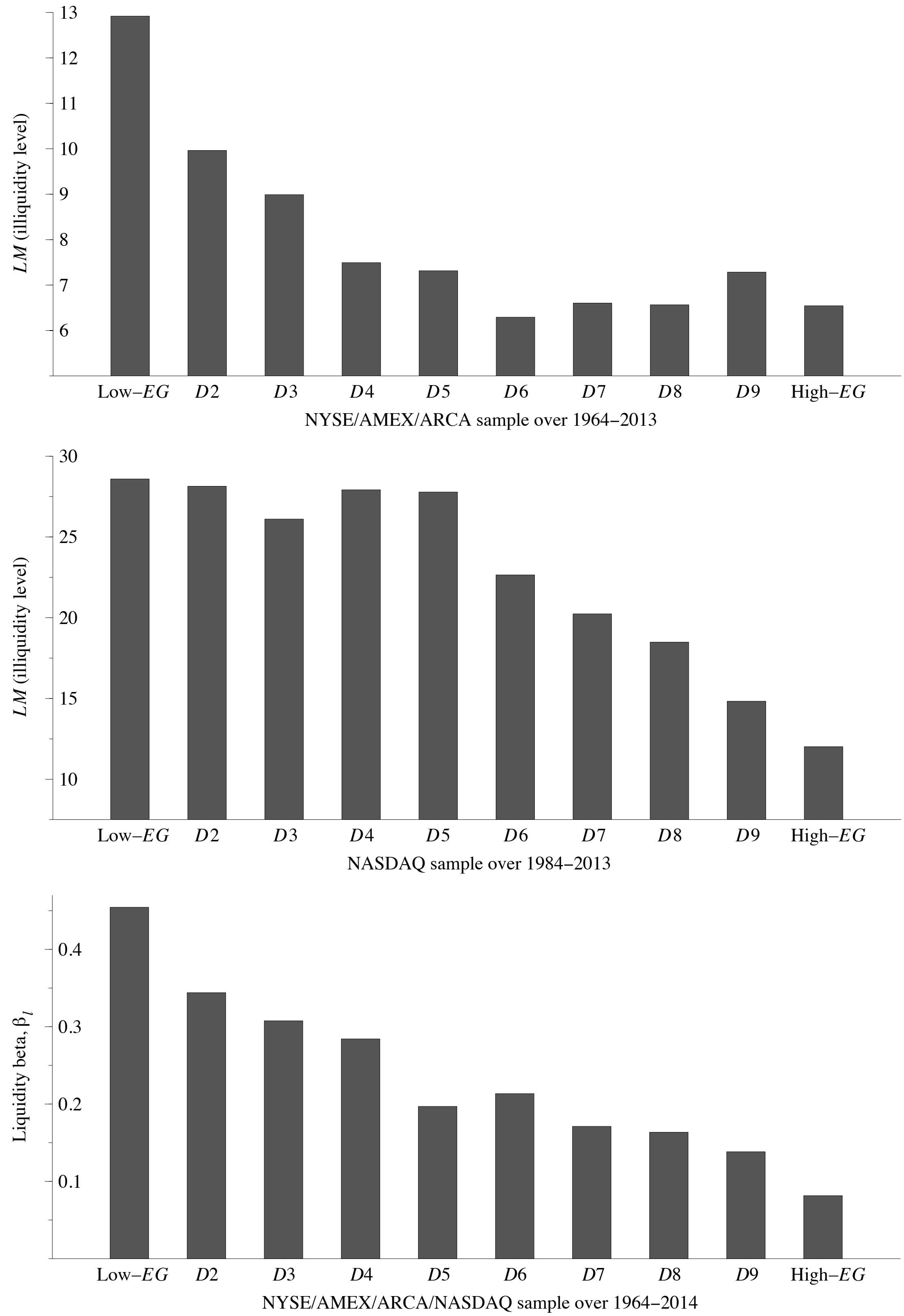

Fig. 1. This figure plots the illiquidity level (i.e., liquidity as a firm characteristic) and liquidity risk (i.e., the loading on the liquidity risk factor) of the decile portfolios formed on employment growth (EG). We form EG portfolios at the end of June each year and hold them for the subsequent 12 months. The symbol LM stands for the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months, and β_l for the loading on the liquidity risk factor of the liquidity-augmented CAPM (LCAPM).