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Disciplines

Finance and Financial Management

Asset Pricing Implications of Hiring Demographics *

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This paper documents that U.S. industries that shift their skilled workforce toward young employees exhibit higher expected equity returns. The young-minus-old (YMO) hiring return spread comoves negatively with value-minus-growth while being significantly positive on average. Exposure to the YMO spread accounts for a significant portion of annual momentum profits at the industry level. I find that an adjustment of the skilled workforce toward young employees is associated with greater productivity in new capital inputs of an industry. This motivates a risk-based explanation for the YMO spread, and its interaction with value and momentum. A model of investment and hiring where young and experienced employees are equipped with differential roles in production and investment can account for the empirical findings.

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1 Introduction

In the evolving technological environment of the economy, firms look for opportunities to improve their existing operations and to expand by investing in new capital. Two features of the workforce stand out for firms' success in these activities: experience in existing operations and openness to new technologies. Experienced employees offer the ability to improve and expand production processes in place, while the best hires for a firm adopting new technologies may be the ones that are less entrenched into the status quo, and are more adapted to recent advancements in technology. The demographic dimension of hiring activity is therefore likely to be informative about the risks and opportunities embodied in future investments.[1]

In this paper, I investigate the asset pricing implications of hiring demographics. My focus is on the skilled workforce (defined as employees with college or higher degrees) because skilled employees are more likely to be confronted by advancements in technology. I find that U.S. industries that shift their workforce toward young, skilled employees earn higher expected equity returns. The average annualized return differential between high and low young-skilled hiring portfolios from 1965 to 2015 is 4.6%. I call the portfolios of industries tilting toward young and old skilled employees portfolio Y and O, respectively.[2] The portfolio strategy long in portfolio Y and short in portfolio O is labeled YMO. Industries exhibit substantial time-series and cross-sectional variation in whether they tilt their workforce toward young or experienced workers. Therefore, no single industry is responsible for the empirical results.

The YMO return spread has an alpha of 5.6% after controlling for Fama and French (1993) factors. It is negatively correlated with the HML (value minus growth) factor, which implies positive comovement between industries that focus on hiring young employees and growth stocks. Because growth stocks have lower returns, unlike stocks in portfolio Y, the HML factor does not explain the

[1]The importance of labor demographics for economic activity is a recent focus in the literature. Some emphasize the causal impact of demographic changes on the business cycle, and argue for capital-skill complementarity (Jaimovich and Siu (2009) and Jaimovich, Pruitt, and Siu (2013)). In contrast, others focus on the benefits of employing young talent in openness to new technologies, young workers' ability to break away from production methods of the past, and adapt to novel business processes (Acemoglu, Akcigit, and Celik (2014) and Liang, Wang, and Lazear (2014)).

[2]I use the phrases old and experienced interchangeably. In general, "young" refers to recent college graduates and "old" or "experienced" refer to all employees that are not in the young group.

average returns of the YMO strategy, and results in a Fama and French (1993) three-factor alpha that is larger than the average YMO spread. Controlling for profitability and investment factors recently proposed by Hou, Xue, and Zhang (2014) and Fama and French (2015) does not alter the results. A well-known feature of the cross-section of industry returns is momentum (Jegadeesh and Titman (1993), Moskowitz and Grinblatt (1999)). The YMO return spread is significantly positively associated with, and helps explain industry momentum (INDMOM) returns.

What is the underlying force responsible for these results? To answer this question, I investigate the interaction between the demographic dimension of hiring and two types of technological progress that are major drivers of economic growth:[3] total factor productivity (TFP), which affects the entire capital stock in place, and investment-specific technology (IST), which is embodied in new capital only.[4] First, the YMO return spread has a significant positive exposure to measures of aggregate IST shocks, while it tends to be negatively associated with TFP shocks.[5] This is in sharp contrast with the HML factor return, which has a positive loading on TFP shocks and a negative loading on IST shocks. The differential exposure of YMO and HML returns to macroeconomic shocks offers an explanation for their negative correlation in the time series while making a joint explanation for YMO and HML returns rather challenging. In addition to being positively correlated, YMO and INDMOM returns exhibit similar comovement with aggregate TFP and IST shocks, suggesting that their positive correlation is driven by their exposure to fundamental shocks. Second, using industry-level data on the relative price of investment goods, I

[3]Greenwood, Hercowitz, and Krusell (1997) find that investment-specific technological change played a major role in post-war U.S. economic growth in addition to neutral productivity growth.

[4]I use the terms TFP and disembodied technology as well as IST and embodied technology interchangeably.

[5]The interpretation of these fundamental shocks is particularly suitable for the question studied in this paper as can be seen in the definitions by Berndt (1990) (also used by Kogan, Papanikolaou, and Stoffman (2016)): "Embodied technical progress refers to engineering design and performance advances that can only be embodied in new plant or equipment. To the extent that technical progress is embodied, its effects on costs and production depend critically on the rate of diffusion of the new equipment, which in turn depends on investment and the resulting vintage composition of the surviving capital stock. By contrast, disembodied technical progress refers to advances in knowledge that make more effective use of all inputs, including capital of each surviving vintage (not just the most recent vintage). In its pure form, disembodied technical progress proceeds independently of the vintage structure of the capital stock. The most common example of disembodied technical progress is perhaps the notion of learning curves, in which it has been found that for a wide variety of production processes and products, as cumulative experience and production increase, learning occurs which results in ever decreasing unit costs. Some have called this type of learning process learning by doing, learning through the examples of others, or learning by using."

show that a shift toward young-skilled employees in hiring activity is a leading indicator of higher technology embodied in new capital formation compared to the rest of the economy over a subsequent medium-term period. This period is also accompanied by higher quantities of investment in capital goods that embody rapid technological progress: equipment, software, and R&D. These patterns are in line with the intuition discussed above: industries facing investment opportunities that embody high levels of technology prefer to populate their skilled workforce with younger employees, while a lower level of embodied technology in new capital is associated with an emphasis on experience in the hiring process.

Motivated by the evidence on the association of hiring demographics with fundamental shocks to technology, I propose a partial equilibrium model of firms where young and old employees have differential roles in production and capital investment. Specifically, I assume that experienced employees are more productive in working with assets in place to capture the benefit of experience in existing operations. Young employees, in contrast, offer an opportunity to reduce capital adjustment costs if the firm is facing higher embodied technology levels in new capital. Therefore, the demographic composition of the workforce has a direct impact on the capital adjustment costs of the firm. The causal chain behind the model mechanism is as follows. A firm faces investment opportunities that embody a high level of technology compared to the rest of the economy. This is characterized by a persistent increase in firm-specific embodied technology consistent with the empirical evidence. Because of the dependence of capital adjustment costs on the composition of labor, the firm optimally decides to hire more young employees.

Firms that desire to adjust most rapidly toward young employees are those most exposed to fluctuations in aggregate embodied technology. Because the adjustment in the composition of labor takes place first, it is a leading indicator of the high-investment period and can therefore serve as a proxy for the conditional exposure to aggregate IST shocks. The model explains the positive average returns for the YMO strategy given a positive market price of risk for aggregate IST shocks. This is consistent with models in which improvements in embodied technology are associated with a decrease in the marginal utility of marginal investors. The average YMO spread constitutes compensation for exposure to technological progress in new capital. In the model, value firms are more exposed to aggregate TFP shocks due to the operating leverage caused by the presence of labor and capital adjustment costs as well as wages that are not very responsive to shocks. Therefore, a positive market price of risk for TFP shocks helps explain the value premium. There is a tension between the impact of IST shocks on average YMO returns and the value premium, because growth opportunities are more positively exposed to aggregate IST shocks compared to assets in place. Hence, a positive value premium arises because the positive impact of exposure to TFP shocks dominates the negative impact of exposure to IST shocks.

This paper is closely related to three strands of literature. First, the relation between labor markets and asset prices is a recent focus in finance. Belo, Lin, and Bazdresch (2014) document that firms with low hiring rates have higher expected returns and explain their findings in a partial equilibrium model using shocks to adjustment costs of the workforce. Belo, Lin, Li, and Zhao (2016) observe that the hiring return spread is largely driven by skilled workers and show that this can be explained assuming costlier adjustment for skilled workers. Ochoa (2013) also argues for costlier adjustment for skilled labor and studies the relation between volatility risk and labor frictions. Kuehn, Simutin, and Wang (2014) show that firms have differential exposures to fluctuations in the aggregate matching efficiency in the labor market contributing to explanations of cross-sectional stock return spreads. Donangelo (2014) studies the impact of labor mobility on asset prices, while Zhang (2015) focuses on the implications of labor-saving technologies for asset prices. Donangelo, Gourio, and Palacios (2015) and Favilukis and Lin (2015) study the impact of operating leverage induced by labor costs on asset prices. The present paper explores a novel dimension of the workforce on asset returns, namely, the demographic structure of hiring dynamics. In the empirical analysis, I show that the relation between hiring demographics and equity returns is different from documented cross-sectional patterns related to hiring and investment. Further empirical evidence on the relation between hiring demographics and technological progress, which I use to construct the model, is consistent with the mechanism driving the asset pricing results.

Second, investment-specific technological progress has become an important feature of economic models starting with Greenwood, Hercowitz, and Krusell (1997). This type of fluctuations in technology has been adopted in recent finance literature. Papanikolaou (2011) studies the implications of IST shocks on asset prices in a two-sector general equilibrium model, while Kogan and Papanikolaou (2013) and Kogan and Papanikolaou (2014) study the implications of IST shocks in partial-equilibrium models. Garlappi and Song (2016) estimate a positive price of risk for IST shocks using a long sample of portfolio returns and relative price of investment in the data. In this paper, I present evidence on the interaction between the implications of hiring demographics and IST shocks, and provide conditions under which the exposure to IST shocks can help explain the positive and significant return spread between industries focusing on young versus experienced employees in hiring. The positive association between industry momentum and the YMO spread is related to Li (2014) who builds a model with investment commitment to explain momentum profits based on their positive exposure to IST shocks. In the model presented in my paper, firms that face favorable IST shocks optimally decide to change the composition of the workforce first, and then increase investment which gives rise to persistent exposure to aggregate IST shocks for winner firms.

Finally, the economic implications of the demographic composition of the workforce is an active area of research in macroeconomics. Jaimovich and Siu (2009) study the implications of the changing labor demographics in the U.S. for business cycle volatility. Jaimovich, Pruitt, and Siu (2013) focus on the differential fluctuations of hours experienced by young and old employees, and argue for capital-experience complementarity. I use this insight to model the differential role of young and old employees in production. Acemoglu, Akcigit, and Celik (2014) find that firms that plan to intensively engage in innovative activity tend to hire younger managers. While I focus on the entire skilled workforce, and a broader definition of technological progress and investment, the causal chain in this paper that young employees sort to firms that have future expectations of high-technology investments is in line with their findings. These papers focus on the role of young and old employees in production like the present paper, but do not study asset pricing implications. Gârleanu, Kogan, and Panageas (2012) study the implications of displacement risk induced by innovation that experienced agents face for the value premium. In their model, growth firms and future generations are beneficiaries of innovation, and innovation constitutes a negative shock to existing agents' human capital. Therefore, growth firms become a hedge against existing agents' income risk. In this paper, I view young and old employees as differential factors of production rather than focusing on their portfolio choice, and consider the firm hiring decisions that depend on the growth opportunities they face.

The paper is organized as follows: Section 2 presents the data, describes the empirical analysis of portfolio returns and their interaction with technology shocks. Section 3 presents the model and shows the results from the calibration exercise. Section 4 concludes.

2 Empirical Analysis

In this section, I present and discuss the empirical evidence on the relation of hiring demographics and the cross-section of stock returns. Section 2.1 presents the data sources used for the main analysis. Section 2.2 describes the formation of portfolios and portfolio characteristics. Section 2.3 starts with the presentation of portfolio returns and analyzes them in the context of factor models, robustness checks, and interactions with other features of the cross-section of returns. Section 2.4 presents evidence on the relation of portfolio returns resulting from hiring policy to momentum profits. Section 2.5 provides evidence on the interaction of the demographics of hiring with macroeconomic shocks and investment which will motivate the model in Section 3.

2.1 Data

The main source for labor market data is the U.S. labor file of the KLEMS data set constructed by Jorgenson, Ho, and Samuels (2012).[6] The data set provides the number of employees and compensation per employee at an annual frequency for U.S. industries. The industry classification follows the international SIC system. All variables are available by education level, age group, and a decomposition into employees and the self-employed. The labor market variables in the KLEMS data set are calculated using the March supplements of the Current Population Survey (CPS) and covers the period from 1947 to 2010. I confirm that the finalized data are closely replicable using the CPS files and extend all variables until 2015. The analysis in this paper uses the series for

[6]KLEMS stands for capital, labor, energy, materials, and services.

private sectors excluding agriculture.[7] This results in a data set consisting of 27 industries, which are listed in Table 1.

I use stock returns from the Center for Research in Security Prices (CRSP) and accounting information from the annual files of the CRSP/Compustat Merged dataset. To match the stock return and accounting data with the labor market data, I use a mapping between the standard industrial classification codes (SIC) from the CRSP/Compustat Merged dataset and the international SIC codes from the United Nations Statistics Division.

2.2 Portfolios

The focus of this paper is the cross-sectional variation in the demographic dimension of hiring activity and its interaction with the differential growth opportunities and technologies faced by firms. For this purpose, I exclusively use data on the skilled workforce as skilled employees are more likely to be confronted with technological progress. Skilled workforce is defined as requiring college completion or higher degrees as in Krusell, Ohanian, Ríos-Rull, and Violante (2000). The key variable capturing the demographic focus of hiring at the industry level is given by $\omega_t = \log(l_t^y/l_{t-1}^y) - \log(l_t^o/l_{t-1}^o)$, where l_t^y is the number of young employees and l_t^o is the number of old employees in year t.[8] This corresponds to the difference between the hiring rates for the young and old workforce.[9]

I use value-weighted monthly stock returns for each industry. To study the link between hiring activity and expected returns, I match ω_t with monthly returns from January to December of year $t+1$. This allows for a gap between the realization of the sorting variable and returns as in Fama and French (1992). To construct portfolios, I sort industries based on ω every year. The young (Y) portfolio consists of five industries with the highest values of ω, namely the industries that shift their skilled workforce toward younger employees the strongest. Analogously, the old (O) portfolio contains the five industries with the lowest ω values. The remaining industries are

[7] Specifically, I exclude the public administration and defense industries, education, and private households with employed persons.

[8] See Appendix B for implications of the level versus changes in the demographic composition of labor.

[9] Another way to interpret ω is the change in the ratio of young to old employees in the industry.

grouped into the medium (M) portfolio. For the main analysis, I use the specification with three portfolios and the age of 29 for the classification of employees into young and old groups. Most accounting variables related to investment and hiring at the firm level are available starting from 1965. The KLEMS data set also seems more reliable from the 1960s, as there is almost no inertia in the time series of variables in this period. The availability and reliability of data results in a final dataset of 600 months from 1965 to 2015. The robustness of the results to perturbations from the baseline case is discussed in Section 2.3.6.

Table 2 summarizes some key characteristics of the Y, M, and O portfolios. The average change in the young-to-old ratio, ω, is 5%, 0% and -6% for the Y, M, and O portfolios, respectively. The average growth of the number of young employees is 8% in portfolio Y while the growth of old employees is only 3%.[10] The average shares of portfolios Y and O in aggregate market capitalization are similar with 18% for the Y and 17% for the O portfolio. The symmetric distribution of average market shares is a result of high turnover: although industries have different average market size shares, there is no industry that dominates a portfolio and drives the results.

Stocks in portfolio Y have a lower average book-to-market ratio (B/M) (0.65) than stocks in portfolio O (0.72). Although the relation is not monotonic with an average B/M if 0.61 for portfolio M, portfolio Y exhibits more growth-like behavior than portfolio O. However, the spread in average B/M is small compared to sorts on B/M itself, where the lowest-quintile portfolio can have an average B/M as low as 0.25 and the highest-quintile portfolio has an average B/M of 1.59.

I also investigate whether adjustments to the demographic composition of the workforce are associated with expansions or contractions in the quantity of the workforce and physical capital, both of which have been found to have a significant impact on the cross-section of equity returns. As Table 2 shows, there is no significant pattern in those quantities, just as there is none in profitability. An important feature of the data is thus that changes in the demographic composition of the skilled workforce are not associated with significant changes for industries at the extensive margin of capital and labor.

[10]Note that the differences in ω are not necessarily driven by firing of young or old employees. In the U.S., about 2% of employees quit their job every month. Therefore, a differential focus in hiring on the young and old is sufficient to generate the observed differences in ω across portfolios.

2.3 Demographics of Hiring and Stock Returns

2.3.1 Portfolio returns

What do adjustments to the workforce demographics imply for the cross-section of stock returns? To answer this question, I compute the monthly value-weighted stock returns of portfolios Y, M, and O from January 1966 to December 2015. Panel A of Table 3 shows that the average annualized excess return of portfolio Y is 9.17%, while it is 4.52% for portfolio O. The return spread between portfolios Y and O (called YMO hereafter) is 4.64% on average and statistically significant with a t-statistic of 3.09.[11] The Sharpe ratios of portfolios are also monotonic with 0.52 for portfolio Y and 0.26 for portfolio O.

Panel B and Panel C of Table 3 report results from CAPM and Fama and French (1993) three-factor (FF-3) regressions of portfolio returns. CAPM provides little explanatory power for the YMO portfolio returns, with an R^2 of 2%, yet it yields a statistically significant coefficient of 0.10 on market excess returns. However, the market exposure is too small to explain the average YMO return, resulting in a CAPM alpha of 4.18%. The FF-3 regressions deliver a striking result: while the explanatory power of the FF-3 model is higher than that of CAPM for the variation in the YMO portfolio returns with an R^2 of 8%, the FF-3 alpha is larger than the average return spread, namely 5.56% with a t-statistic of 3.64. This stems from a significant negative loading of -0.30 on the value-minus-growth (HML) factor. The returns of portfolio Y comove positively with value and negatively with growth stocks, while portfolio O exhibits the opposite behavior. Figure A.11 plots the 5-year average monthly YMO returns and the corresponding FF-3 alphas. The YMO returns is positive in the vast majority of 5-year periods, and is high in both the earlier and the later subsamples.

The conclusion from the results in Table 3 is not only the failure of the unconditional CAPM and FF-3 models to explain the YMO return spread but also the spread's interaction with the well-studied value premium, namely that value firms have significantly higher average returns than growth firms. Portfolio Y has high average returns despite more "growth-like" behavior in terms

[11] All t-statistics are based on Newey-West standard errors with six lags in monthly data unless otherwise stated.

of its factor loadings, while growth (low B/M) firms have lower returns. This observation is key for the choice of model ingredients presented in Section 3 to explain the YMO spread consistent with the empirical evidence. The factor regressions thus provide valuable information about the set of potential risk-based explanations for the YMO spread.[12]

2.3.2 Alternative factor models

Recent literature has modified the FF-3 model by factors related to investment and profitability. Hou, Xue, and Zhang (2014) propose a four-factor model motivated by a simple version of the q-theory, which predicts a negative relation between investment rates, and a positive relation between profitability and expected returns. As shown in Panel A of Table 4, the implications of the q-factor model for the YMO return spread are similar to those of the FF-3 model. The q-factor alpha is 5.72%, and the loading of the YMO spread on the investment factor, which has a correlation of 69% with the HML factor of the FF-3 model, is negative. Fama and French (2015) (FF-5) extend the FF-3 model by the investment and profitability factors motivated by the fact that the FF-3 model does not explain the positive average returns of strategies based on investment and profitability. Panel B of Table 4 shows that the FF-5 model delivers results similar to those of FF-3. Specifically, the loadings of the YMO return on profitability and investment factors are small and insignificant, while the negative loading on HML remains significant and its magnitude does not change significantly. The FF-5 alpha of the YMO spread is 6.16% with a t-statistic of 3.64.

2.3.3 Firm-level predictability

Next, I investigate the predictive ability of ω at the firm level. To do this, I assign the industry-level value for ω to all firms in the same industry every year. I use investment rates (I/K), hiring rates (H/N), and B/M from accounting data to assess the marginal predictability of ω. Table 5 shows that ω has predictive power for annual stock returns: a 10 percentage point increase in ω (which is close to a one standard deviation increase based on the unconditional volatility of ω at

[12]See Table A.17 for results from rolling factor regressions.

the industry level) is associated with a 1.5 percentage point increase in the firm's annual stock return. The magnitude of this effect does not change significantly when controlling for I/K, H/N, and B/M.

2.3.4 Double sorts

Table 6 reports results from double sorts based on ω and other characteristics that are known to predict returns in the cross-section of stocks. To do this, I maintain the classification of industries into portfolios Y, M, and O as in the baseline analysis and sort stocks based on another characteristic within these portfolios using NYSE breakpoints.[13] To summarize, the YMO return spread is positive in all double sorts, while its magnitude and statistical significance varies. The YMO spread is larger among growth (low B/M) stocks (4.66%) than among value (high B/M) stocks (2.57%). The value premium is large in all portfolios Y, M, and O, while it is statistically significant in M and O.[14] Unlike many cross-sectional return dispersions, the YMO spread is not concentrated in small stocks. The YMO spread is also largest among low hiring and investment portfolios, while it is large and significant among medium portfolios of these categories as well. High investment and high hiring portfolios also have positive YMO spreads, while their statistical significance is low. The FF-3 factor model has explanatory power for book-to-market, size, investment, and employment growth sorts while it does not for YMO in double sorts. Overall, the YMO spread is positive among various sets of stocks grouped by characteristics known to predict returns. It is strongest among the growth, non-micro cap, low to moderate investment and hiring groups.

2.3.5 Exposure to YMO

As discussed in Section 2.2, portfolios are not dominated by certain industries. To summarize the information about industries' exposure, I regress 49 industry excess returns on the YMO return and

[13] Two-way sorts and sorts first on another characteristic and then on ω deliver very similar results.

[14] The presence of a value premium in portfolios Y, M, and O is consistent with Cohen, Polk, and Vuolteenaho (2003) who find that the book-to-market effect in returns is mostly an intra-industry effect.

report five industries with the highest and lowest exposures in Table 7.[15] High exposure industries tend to be in high-technology areas such as computer software and hardware development, as well as measuring, control, and electronic equipment. While the machinery, shipbuilding and railroad equipment, and petroleum industries are among the most exposed in the earlier half of the sample (1966 - 1989), high-technology industries are the most exposed in the second half of the sample (1990 - 2015). The focus on young and skilled workers in hiring activity is thus concentrated in areas of rapid technological progress, especially over the last 25 years. Industries with the lowest exposure to YMO, such as plastic products, entertainment, food, and accommodations, are less likely to depend on ongoing technological progress.[16]

2.3.6 Robustness checks

To check the robustness of the findings, I conduct several robustness tests and report the results in Table 8. I split the sample into two equally sized periods, taking December 1989 as the last observation of the first subsample. The average YMO spread in the first and second halves of the subsample is 5.41% and 4.44% with t-statistics of 2.30 and 2.39, respectively. Most studies omit financial firms because the characteristics of financial firms, such as investment, have a different economic content compared to regular firms. Omitting the financial and real estate industries results in an average YMO spread of 3.96% with a t-statistic of 2.60. There is a positive relation between R&D expenditures and stock returns among firms that report positive R&D expenditures (Chan, Lakonishok, and Sougiannis (2001), Li (2011)). This relation is particularly relevant for an interpretation based on exposure to technological progress because R&D activities embody new technologies by definition. I exclude all firms that report positive R&D expenditures in Compustat. The YMO spread after this omission is 3.48% and statistically significant, which implies that the YMO spread is not entirely driven by cross-sectional differences related to high R&D industries but holds more generally for all industries. Finally, I set the age for classification into young and

[15] I use 49 industry returns from Kenneth French's website.

[16] The average returns of five highest-exposure industries is not statistically different from the ones with lowest exposure to YMO, or the aggregate market return. Thus, time variation in portfolios is important to capture the positive average YMO return.

old to 35 and still obtain a YMO return spread of 3.71%. Another concern is the definition of skill. For main results, I defined skilled employees as those who hold at least a college degree. However, a college degree in 1960's represents a better place in the skill distribution of the workforce than it does today. Therefore, I split the education distribution into its upper and lower half every year such that, say, a high school graduate is in the skilled group in 1960's, but not in 2000's. Table 8 shows that main results remain unchanged using this definition of skill. A notable common feature of the YMO spread in all robustness checks is its negative loading on the HML factor as shown in Panel B of Table 8. This results in FF-5 alphas that are larger than the YMO spread in all cases.

Table 9 shows the benchmark results for five portfolios formed on ω. For this exercise, I keep the Y and O portfolios the same as in the baseline case and split portfolio M into portfolios 2, 3, and 4 containing five, seven, and five industries, respectively. The excess returns, CAPM, and FF-3 alphas of the five portfolios monotonically increase in ω, while the differences in the average returns of portfolios 2, 3, and 4 are not statistically significant. Finally, I investigate the behavior of portfolio returns at the annual frequency and report the results in Table 10. The results are similar to the case using monthly returns (Table 3). Specifically, the CAPM and FF-3 alphas are positive and significant despite the lower number of observations. The loading of the YMO spread on the HML factor in annual data is significantly negative and slightly larger than in the monthly data in absolute value.

2.4 Relation to industry momentum

A striking feature of the cross-section of returns is persistence, commonly referred to as momentum. Jegadeesh and Titman (1993) document that stocks with high recent performance (winners) continue to have higher returns compared to stocks with low recent returns (losers). The literature has investigated the properties of momentum for stocks and other asset classes extensively, and most existing theoretical explanations are behavioral, such as underreaction to information.[17]

The YMO spread has a correlation of 16% with the UMD factor at both the monthly and

[17] See Jegadeesh and Titman (2011) for an overview.

annual frequency.[18] The correlation is particularly high when the bursting of the tech bubble and the Great Recession are excluded. Specifically, it is 34% at the monthly frequency and 58% at the annual frequency in the sample from 1966 to 1999. This is because of the negative comovement between YMO and UMD during "momentum crashes," namely prolonged periods of low momentum performance following large market downturns as studied in Daniel and Moskowitz (2016). Figure 1 demonstrates this point by plotting the annual dynamics of normalized YMO and UMD returns in the upper panel and the three-year average dynamics in the lower panel. Momentum returns and the YMO spread closely track each other, with the most notable exception of the Great Recession period.

Despite their high degree of comovement, the YMO spread does not provide a full explanation for momentum profits captured by UMD when used as a factor. The average UMD return is 8.57% (11.92%) in the period from 1966 to 2015 (1966 to 1999). When regressed on the YMO spread, it still has an alpha of 7.55% (9.31%). However, the direct comparison of YMO and UMD may be misleading for two reasons. First, the UMD factor is constructed using portfolios rebalanced at the monthly frequency (based on prior 2- to 12-month returns), while the YMO spread is computed rebalancing portfolios at annual frequency because of the availability of labor market data. Second, UMD is constructed using individual stock price momentum, while the YMO spread is computed from industry returns as described in Section 2.2. The first point can be addressed by changing the frequency of portfolio rebalancing and is related to the persistence structure of momentum profits. Novy-Marx (2012) shows that strategies based on past 6- to 12-month returns deliver higher average returns compared to the profits of strategies based on very recent performance in the past two to six months. The second point is particularly interesting in the context of momentum profits, as Moskowitz and Grinblatt (1999) document that high momentum returns can be achieved at the industry level, explaining a large fraction of momentum profits at the individual stock level.

Addressing these points may help project momentum profits to a comparable space as the YMO spread. Therefore, I analyze industry momentum (INDMOM) portfolios with annual rebalancing

[18] The UMD factor is available from Kenneth French's website.

and report the results in Table 11. First, I use the 30 industry portfolio returns from Kenneth French's website (Panel A). In light of Novy-Marx (2012)'s findings, I sort industries based on returns from January to July of year t and compute returns in year $t+1$ for the baseline analysis. I also analyze INDMOM profits based on returns from July to December of year t and compute quantities for the samples from both 1966 to 2015 and 1966 to 1999.[19] Five winner industries outperform five loser industries by an average return of 4.48%, with statistically significant CAPM and FF-3 alphas of 3.43% and 5.13%, respectively. The correlation between YMO and INDMOM is 33%, which is higher than the correlation of 16% with UMD. As shown in Figure 2, the increase in the correlation is primarily driven by the large crash in UMD during the Great Recession that is absent in INDMOM and YMO. To understand whether industry momentum accounts for the comovement between UMD and YMO, I regress UMD on INDMOM (which delivers an R^2 of 13%) and compute the OLS residuals. The residual of UMD after this orthogonalization has a correlation of only 4% with YMO, which suggests that the common component of YMO and UMD is primarily driven by the industry component of momentum profits.

While industry momentum has significant CAPM and FF-3 alphas, the market return and the YMO spread account for about half of it, leading to an alpha of 2.28% with a t-statistic of 1.50. Table 11 also shows that the difference between the average INDMOM returns and alphas after the inclusion of YMO as a factor in time series regressions is even larger in the sample from 1966 to 1999 (which is close to the sample used by Moskowitz and Grinblatt (1999) to study industry momentum) and when the industry classification follows the international SIC divisions. The YMO spread, which is constructed using information on the hiring policies of industries along the demographic dimension, thus provides a potential explanation for INDMOM. This result occurs when INDMOM is computed using the same frequency and granularity of information as the computation of the YMO spread. Winner industries behave similarly to industries hiring young-skilled employees, while losers tend to favor experienced workers. I leave further investigation of how to make YMO more operational to test explanations of momentum profits for future research.

[19] I repeat the analysis using the international SIC classification used to construct the YMO returns and report results in Panel B of Table 11.

2.5 Relation to macroeconomic shocks and investment

This section provides evidence on the relation of portfolio returns on fundamental shocks. Section 2.5.1 assesses the exposures of YMO, HML, and INDMOM returns to aggregate TFP and IST shocks. Section 2.5.2 presents an empirical relation between the demographics of hiring and IST shocks in the cross-section of industries.

2.5.1 Aggregate shocks

The driving force in most investment-based models of the cross-section of returns is differences in exposure to total factor productivity (TFP) (e.g., Gomes, Kogan, and Zhang (2003), Zhang (2005)). A recent strand of literature emphasizes the role of investment-specific technology (IST) shocks as a potential source of risk driving cross-sectional differences in expected returns (e.g., Papanikolaou (2011), Kogan and Papanikolaou (2013), Kogan and Papanikolaou (2014)). While TFP shocks affect the productivity of all assets in place, IST shocks are embodied in new capital goods. I summarize the evidence on the exposure of the YMO spread in this section and use it to construct the model in Section 3.

I use annual data on TFP from Fernald (2014), available from the Federal Reserve Bank of San Francisco website, for TFP shocks (Δa). Innovations in the price of investment goods relative to consumption goods provide a proxy for IST shocks (Greenwood, Hercowitz, and Krusell (1997)). Specifically, the relative price of new equipment exhibits a downward trend in the postwar U.S. data. This represents the expanding investment opportunity set in the economy driven by the technological progress in new capital goods. Firms profit from and expose themselves to such technological progress to the extent that they invest and form new capital (see Section 3 for a more detailed discussion). I use the inverse of the quality-adjusted relative price of equipment constructed by Israelsen (2010) to compute the first measure of IST shocks (Δz). The second measure of IST shocks is the equity return differential between investment and consumption goods-producing sectors in the U.S. economy. This return differential serves as a proxy for investment shocks under the assumption of a two-sector model where the consumption sector buys investment goods from the investment goods sector to expand capital (Papanikolaou (2011)). While a perfect empirical classification of firms into investment and consumption goods producers is difficult, as most industries produce both types of goods, Gomes, Kogan, and Yogo (2009) propose a methodology based on the majority of sales for every industry, which I use to compute the return differential between the investment and consumption sectors (R_{imc}).

Table 12 reports results from time series regressions of YMO, HML, and INDMOM returns on proxies of TFP and IST shocks, which I normalize to have unit standard deviation. I consider three specifications. The first one computes the return exposures to Δa and Δz. The YMO spread has a negative loading on Δa, which is large but not statistically significant, while it has a positive and significant loading on Δz. Specifically, a one standard deviation shock to Δz leads to a 4% higher contemporaneous YMO spread on average. The loading of the HML return on Δa is positive and significant, while it is negative and not significantly different from zero for Δz. Next, I replace Δz by R_{imc}. This increases the joint explanatory power of TFP and IST shock proxies for all three returns considered in this section. The negative loading of the YMO return on Δa does not change significantly in magnitude compared to the first specification, but it becomes statistically significant. The YMO return has a significantly positive loading on R_{imc}, as it does on Δz. While the HML return has a positive and significant loading on Δa, its loading on R_{imc} as a proxy for IST shocks is negative and highly significant. A one standard deviation increase in R_{imc} corresponds to a contemporaneous 2% drop in the annual HML return.

The exposure of returns to macroeconomic shocks sheds some light on the comovement between YMO and HML discussed in the previous sections. The opposite loadings of the YMO and HML on fundamental shocks can explain the negative comovement between these two long-short portfolio returns. At the same time, the significant and opposite loadings on macroeconomic shocks are informative about potential joint explanations of positive average returns for YMO and HML strategies. I use these results to discipline the model in Section 3 that can explain the positive expected returns of YMO and HML, while being consistent with the association of returns with macroeconomic shocks.

Finally, INDMOM has a negative loading on Δa, while its exposure to Δz is not statistically different from zero. The loadings of INDMOM on Δa and R_{imc} are similar to those of YMO. The positive comovement of YMO and INDMOM is also consistent with their loadings on TFP and IST shocks, especially when R_{imc} is used as the proxy for IST shocks.

The last specification uses the aggregate excess market return (R_m) and R_{imc} as the right-hand variables. The loadings of YMO, HML, and INDMOM on R_m are not statistically different from zero, while the loadings on R_{imc} are very close to the second specification where I include Δa instead of R_m.

2.5.2 IST shocks and investment at the industry level

The nature of investment goods that industries need is different and varies over time, so it is natural to expect that there is heterogeneity in the technology levels embodied in new capital across industries. Is there any association between investment opportunities and the demographic dimension of hiring policy? In this section, I provide some direct evidence that answers this question beyond the return-based evidence discussed in Section 2.5.1. I use the inverse of the relative price of investment at the industry level as the proxy for the embodied technology level. The KLEMS data set provides quality-adjusted price indices for capital services at the industry level and annual frequency. I divide these by the consumption deflator to compute the relative price of investment at the industry level.[20] The price indices in KLEMS include all investments, while the aggregate index from Israelsen (2010) used in Section 2.5.1 includes only equipment investments, namely investment goods with the fastest technological progress. Despite this caveat, the relative price of investment computed from KLEMS falls steadily in the postwar period.[21] It also preserves the interaction of IST shocks with returns as reported in Section 2.5.1. Aggregate IST shocks computed from KLEMS data have a correlation of -29% with HML and 33% with YMO (compared to -5% and 22% using the equipment price data from Israelsen (2010) and -62%

[20] I use the consumption deflator data from the Federal Reserve Bank of St. Louis (FRED).

[21] Unlike equipment and software, the relative price of structure investment does not decrease in the postwar period (Jermann (2010)). Considering the fact that, a large portion of gross private investment is in structures, the inclusion of structures makes the decline in the relative price of investment from KLEMS data less pronounced compared to equipment only. The growth rate of the aggregate IST level is 0.88% in the KLEMS data with an annual volatility of 3.2%.

and 47% using R_{imc}).

For each of the 27 industries listed in Table 1, I compute the inverse of the relative price of investment (called industry IST level hereafter). To compute the IST level for portfolios Y, M, and O, I weight industry IST levels using the quantity of total investment for each industry. I normalize the portfolio IST levels to one four years before portfolio formation and track the pattern of portfolio IST levels until nine years after portfolio formation. Figure 3 illustrates the average dynamics of embodied technology from this exercise at the portfolio level. The average IST levels of portfolios are similar before the portfolio formation year. From the portfolio formation year onwards, the IST level of industries in portfolio Y start to deviate upward, while it deviates downward for portfolio O relative to portfolio M. In other words, industries that shift their skilled workforce toward young employees experience a contemporaneous and subsequent rise in the embodied technology level in new capital goods. The divergence of portfolios continues until about five years after portfolio formation, when portfolio Y experiences a 3.5% increase in IST level while portfolio O's IST level drops by 4% relative to portfolio M. The difference between the growth of IST technology of portfolios Y and O in the portfolio formation year has a t-statistic of 2.01, while the average difference in cumulative growth rates in the five years upon portfolio formation has a t-statistic of 1.81.[22]

Table 13 provides further evidence that demographic shifts predict investment growth in equipment, software, and R&D. A one standard deviation increase in ω predicts 6.61 percentage points higher investment growth over the last year, and 14.75 percentage points higher investment growth over the last three years at the industry level. As shown in Table 14, however, demographic shifts are not associated with future investment in structures.[23] These results are robust to controlling

[22]The exercise that results in Figure 3 treats all industries as consumption goods producers in a two-sector economy such as the one in Papanikolaou (2011). However, some industries have a higher share of their output sold as investment goods. If the relative prices of investment and output of an industry drop at the same time, the industry may not have a net profit from technological progress. To address this issue, I use the price indices of value added for each industry (instead of the consumption deflator) to compute the relative price of investment at the industry level. The resulting average IST levels are plotted in Figure A.1. While the IST levels are less stable before portfolio formation, one can observe a divergence in the IST levels of portfolios Y and O upon portfolio formation similar to that shown in Figure 3.

[23]The positive relation between demographic shifts and investment in structures is completely subsumed by year fixed effects. This is because young-skilled hiring in the aggregate economy is more procyclical than old, and therefore associated with aggregate investment growth.

for past investment rates (Table A.4), and supports more directly the idea that industries hire a younger skilled workforce, when they are expected to increase investments in types of capital that embody new technologies.

The association between a focus on young, skilled employees in hiring policy and a period of higher embodied technology is informative about the relation between hiring demographics, risks, and investment opportunities faced by industries. The pattern depicted in Figure 3 can arise because of an acceleration in the embodied technology in the types of capital that an industry invests in. For instance, an industry may rely heavily on the usage of computer and software, which constitute types of capital with rapid technological progress. An acceleration in the decline of the relative prices of computer and software results in an increase in the embodied technology levels, as shown for portfolio Y in Figure 3. Another possibility is that young and skilled hiring is associated with a shift in investment opportunities toward types of capital where technological progress is faster. Even if there is no change in the aggregate embodied technologies of, say, structures and equipment, an industry may enter a period of modernization in equipment, and the competitive forces in the industry may lead to higher investment in equipment, increasing the observed embodied technology in new capital. Finally, these two mechanisms can reinforce each other. Fast technological progress in new capital goods lower the relative price of investment goods for an industry. Lower prices for new capital goods can incentivize higher investment because of a substitution effect, and firms may also need to invest in new capital to keep up with the industry-wide technological progress. Both of these forces result in an increase in the observed embodied technology levels for an industry.

While it is not possible to disentangle the channels affecting the relative price of investment completely, I investigate the presence of the effect on the quantity of investment by repeating the same exercise as illustrated in Figure 3 for the quantity of investment in equipment, software, and R&D at the portfolio level and plot the results in Figure 4. Industries in portfolio Y start to increase investment after adjusting workforce toward young, skilled employees. This increase takes about three years on average. This is a confirmation that higher embodied technology levels for portfolio Y are also associated with an increase in the quantity of investment in areas where technological progress is prevalent. Furthermore, the association of demographics shifts with future investments tend to operate through the investment shock channel. Table 15 shows that the positive association between future investment growth and current demographic shifts is largely attributable to the interaction of the quantity of investment with investment shocks. A significant portion of the loading of current young-old hiring differential on investment growth over the next three years is explained by an interaction term in the embodied technology level of investments over the next three years.[24] This can be interpreted as follows: the composition of the skilled workforce shifts toward young people when high investment is expected, especially when the expected investments embody a higher productivity level. Therefore, the shift of demographic composition toward young employees serves as an early indicator of exposure to productivity risk embodied in future vintages of capital.[25]

3 Model

This section presents a partial equilibrium model where young and old employees are differential inputs for firms in terms of their role in production and capital investment. Section 3.1 introduces the firm production technology, capital and labor adjustment costs. The roles of labor demographics are also presented in this section. Section 3.2 describes the stochastic processes driving the economy, and Section 3.3 specifies wages and the stochastic discount factor. Section 3.4 describes the firm's problem. The model calibration is presented in Section 3.5 followed by asset pricing results in Section 3.6. Finally, Section 3.7 discusses some extensions of the baseline model.

3.1 Firm Technology

There is a large number of ex-ante identical firms in the economy that produce a homogeneous good. In this section, I describe the technology of a single firm that makes investment and hiring

[24]Table A.7 repeats this exercise with TFP shocks. While TFP shocks have no significant association with demographic shifts, the investment-w relation is weaker when industry-level TFP is high.

[25]See Table A.12 for statistics about firm entry and exit in the industries grouped by portfolio Y, M, and O.

decisions.[26]

The firm produces output y_t using capital and labor inputs, k_t and n_t, according to the following production function:

$$y_t = u_t a_t k_t^{\alpha_k} n_t^{\alpha_n}, \tag{1}$$

where a_t is the aggregate productivity (TFP), which is identical for all firms, and u_t denotes firm-specific productivity. Aggregate and firm-specific productivity determine the firm's disembodied technology level, namely the productivity of all assets in place. α_k and α_n control the sensitivity of production to capital and labor. I assume $\alpha_k + \alpha_n < 1$, which implies decreasing returns to scale at the firm level.

The labor input of the firm is given by

$$n_t = e_y \, l_t^y + e_o \, l_t^o, \tag{2}$$

where l_t^y is the number of young employees and l_t^o is the number of old employees. Each young and old employee provides the firm with efficiency units of e_y and e_o, respectively. Given the efficiency units, the inputs by young and old employees are perfectly substitutable. In the quantitative assessment of the model, I assume $0 < e_y < e_o$, namely that an old employee is more productive in the existing operations of the firm using assets in place. This captures the fact that old employees are more experienced in working with the capital that has been installed in the past.[27]

The law of motion for the firm's capital is given by

$$k_{t+1} = (1 - \delta) \, k_t + i_t z_t, \tag{3}$$

where δ is the depreciation rate per period. The firm expands capital through investment expenditures i_t. The investment-specific technology (IST) level z_t determines how much effective capital the firm can build per unit investment expenditure. The IST level is isomorphic to vintage-specific

[26] I do not use firm subscripts, as all firms in the economy operate according to the same technology.

[27] Jaimovich, Pruitt, and Siu (2013) also view young and old employees as differential factors of production. Their model of the production function assumes a lower degree of complementarity with capital for hours provided by young employees compared to old employees. I opt for the simple specification of perfect substitutability yet differential efficiency units for the purposes of this paper.

productivity and is embodied in new capital built through investment. I assume that the embodied technology is given by

$$z_t = \tilde{z}_t \, z_t^a, \tag{4}$$

where $\tilde{z}_t$ is the firm-specific component and z_t^a is the aggregate IST level, which is identical for all firms.[28] For each firm, I assume $\mathbb{E}[\tilde{z}_t] = 1$, while z_t^a grows over time.[29] This implies that the embodied technology at the firm level fluctuates around the aggregate embodied technology level. Depending on whether the firm-specific component is above or below one, the firm faces an embodied technology that is higher or lower than the average firm in the economy.

One can interpret the firm-specific component $\tilde{z}_t$ as the productivity of firm investment opportunities relative to the rest of the economy. A firm with a high level of $\tilde{z}_t$ faces a technology level in investment opportunities that is less likely to have been experienced by the average firm in the economy. A low level of $\tilde{z}_t$, in contrast, represents a technology level that is more likely to have been experienced by the average firm in new capital formation.

Hiring decisions in the present model are intertemporal, as is capital investment. The laws of motion for the quantity of young and old employees are given by

$$l_{t+1}^y = (1-s)\, l_t^y + h_t^y, \tag{5}$$

and

$$l_{t+1}^o = (1-s)\, l_t^o + h_t^o, \tag{6}$$

where s is the separation rate per period. The quantities of young and old labor hiring are given by h_t^y and h_t^o, respectively. The quantity of hiring can be negative, which occurs in cases where firms want to lower the number of employees more than implied by the separation rate s.

Hiring and firing are costly processes for various reasons: new employees may need training, hiring involves vacancy advertising and a search for new employees, and separations result in the loss of firm-specific human capital that new employees need to accumulate. I assume the following

[28] In recent work, Dou (2016) studies the impact of uncertainty in firm-specific IST shocks on asset prices.

[29] See Section 3.2 for the stochastic processes of technology variables.

quadratic adjustment cost function for labor to capture these features of the hiring process:

$$\Psi_t^n = c_n \left(\frac{|h_t^y| + |h_t^o|}{n_t} \right)^2 n_t, \tag{7}$$

where c_n is a constant. Labor adjustment costs are quadratic in a measure of labor turnover and scale with the size of the labor input of the firm.

I also assume the presence of capital adjustment costs given by

$$\Psi_t^k = c_k (1 + \Psi_t^z) \, \bar{\Psi}_t^k, \tag{8}$$

where c_k is a constant. Capital adjustment costs have two components: $\bar{\Psi}_t^k$ denotes average adjustment costs and Ψ_t^z is a factor that scales average adjustment costs.

Capital adjustment costs are usually motivated by disruption costs caused by the installation or replacement of capital, delivery lags, and time to build. To capture these, I assume a standard quadratic form for average adjustment costs given by

$$\bar{\Psi}_t^k = c_k \left(\frac{i_t z_t^a}{k_t} \right)^2 \frac{k_t}{z_t^a}, \tag{9}$$

where c_k is a positive constant and $\frac{k_t}{z_t^a}$ is the replacement cost of capital at the average value of the firm-specific IST level.[30]

Another factor of capital adjustment costs is costly learning because of changes in the structure of production (Cooper and Haltiwanger (2006)). Such costs have two major dimensions. First, adoption can be costly to the extent that the technology gap is large between firm assets in place and new capital formed through investment. The second dimension depends on the characteristics of the workforce inside the firm, namely how open the employees are to the disruption characterized by the technology gap. To capture these two dimensions of technology adoption, I assume the following form for Ψ_t^z:

$$\Psi_t^z = c_z \left(\tilde{z}_t - 1 \right) \frac{l_t^y}{n_t}, \tag{10}$$

where c_z is a constant and I consider the case $c_z < 0$. Recall that $\mathbb{E}\left[\tilde{z}_t\right] = 1$. If a firm's investment

[30]The z_t^a terms make capital adjustment costs grow at the same rate as other cash flow components. See Appendix D for details.

opportunities embody a higher technology level than the average firm in the economy ($\tilde{z}_t > 1$), the firm has an opportunity to lower capital adjustment costs in addition to achieving higher efficiency of investment because of the role of z_t in (3). The adjustment cost savings are increasing in the fraction of young employees in the firm's workforce. However, if the firm is facing lower levels of embodied technology ($\tilde{z}_t < 1$), investment becomes costlier. The presence of a high fraction of old employees mitigates the additional costs of capital adjustment in this case.

The assumption of lower adjustment costs in the case of high embodied technology levels strengthens the effect of investment-specific technology on real investment opportunities.[31] Furthermore, this specification allows for an interaction between the efficiency of technology adoption characterized by adjustment costs and the composition of the workforce. As discussed above, high levels of $\tilde{z}_t$ can be interpreted as the presence of investment opportunities that embody a technology level that has not been experienced widely in the economy. The adjustment cost factor specified in (10) implies that firms with a younger workforce have an advantage in this case: they can adopt new technologies at a lower cost. This captures the idea that young college graduates are less entrenched in the status quo of existing firm operations and are more open to learning about and adapting to new technologies.[32] If the firm faces a lower level of embodied technology in new capital compared to the average firm in the economy, this technology level is likely to have been embodied in older vintages of capital as well. In other words, the technology gap between new capital and existing assets in place is not large. Older employees have more experience with such capital and therefore constitute a comparative advantage to the firm compared to younger employees.

[31] This specification is similar to models where (positive) investment-specific technology shocks are modeled as (negative) shocks to adjustment costs instead of specifying them in capital accumulation directly. See, e.g., Belo, Lin, and Bazdresch (2014).

[32] This is closely related to Acemoglu, Akcigit, and Celik (2014), who study the relation between manager age and firms' openness to innovation and technology adoption. They find firms that are more "open to disruption" tend to hire younger managers. The notion of employees and technology in this paper is more general (all skilled employees and all investments are considered rather than managers and firm innovation only), but high $\tilde{z}_t$ firms can be considered open to disruption, and such firms will optimally choose to hire younger employees because of the assumptions on the structure of adjustment costs. This is in line with the causal chain in the findings of Acemoglu, Akcigit, and Celik (2014) that young managers are not necessarily making firms more open to innovation, but such firms decide to hire young managers.

3.2 Stochastic processes

The logarithm of aggregate disembodied technology (TFP) follows a random walk with drift:

$$\log\left(\frac{a_{t+1}}{a_t}\right) = \mu_a + \sigma_a \epsilon^a_{t+1}, \tag{11}$$

where μ_a is the drift, σ_a is the conditional volatility, and ϵ^a_{t+1} is a random shock that follows an *iid* standard normal distribution. The logarithm of firm-specific productivity follows an AR(1) process:

$$\log(u_{t+1}) = (1-\rho_u)\bar{u} + \rho_u \log(u_t) + \sigma_u \epsilon^u_{t+1}, \tag{12}$$

where ρ_u denotes persistence, $\bar{u}$ is the unconditional mean of log productivity, σ_u is the conditional volatility, and ϵ^u_{t+1} is a standard normal variable that is *iid* over time and across firms.

The logarithm of aggregate embodied technology (IST) follows a random walk with drift as well:

$$\log\left(\frac{z^a_{t+1}}{z^a_t}\right) = \mu_z + \sigma_z \epsilon^z_{t+1}, \tag{13}$$

where μ_z is the drift, σ_z is the conditional volatility, and ϵ^z_{t+1} a random shock that follows an *iid* standard normal distribution. The logarithm of firm-specific embodied technology follows an AR(1) process:

$$\log(\tilde{z}_{t+1}) = (1-\rho_z)\bar{z} + \rho_z \log(\tilde{z}_t) + \sigma_{\tilde{z}} \epsilon^{\tilde{z}}_{t+1}, \tag{14}$$

where ρ_z denotes persistence, $\bar{z}$ is the unconditional mean of the log IST level, $\sigma_{\tilde{z}}$ is the conditional volatility, and $\epsilon^{\tilde{z}}_{t+1}$ is a standard normal variable that is *iid* over time and across firms.

3.3 Wages and the stochastic discount factor

The present model provides a partial equilibrium description of a single firm. Therefore, I specify wages and the stochastic discount factor (SDF) exogenously, and assume that all firms in the economy face identical wage and SDF dynamics.

The model assumptions in Section 3.1 and 3.2 imply that the number of employees inside the firm grows over time. Following Belo, Lin, and Bazdresch (2014), I assume stationary wage rates such that the wage bill of the firm and output follow the same balanced growth path. The wage rate of young employees is given by

$$w_t^y = \bar{w}^y \exp(\tau_a^y \Delta \log(a_t) + \tau_z^y \Delta \log(z_t^a)), \tag{15}$$

where $\bar{w}^y$ controls the wage level, while τ_a^y and τ_z^y determine the sensitivity of wages to aggregate TFP and IST shocks, respectively. Analogously, the wage rate of old employees is given by

$$w_t^o = \bar{w}^o \exp(\tau_a^o \Delta \log(a_t) + \tau_z^o \Delta \log(z_t^a)). \tag{16}$$

In the quantitative assessment of the model, I calibrate the wage process based on empirical evidence as discussed in Section 3.5.

I specify a log-linear SDF in aggregate disembodied and embodied shocks:

$$M_{t,t+1} = \exp(-r_f) \frac{\exp(-\lambda_a \sigma_a \epsilon_{t+1}^a - \lambda_z \sigma_z \epsilon_{t+1}^z)}{\mathbb{E}_t \left[\exp(-\lambda_a \sigma_a \epsilon_{t+1}^a - \lambda_z \sigma_z \epsilon_{t+1}^z)\right]}, \tag{17}$$

where r_f is the constant risk-free rate, λ_a is the market price of TFP risk, and λ_z is the market price of IST risk.[33] While the SDF in the present model is specified exogenously, the literature offers some guidance on the economic content of market prices of risk. In general equilibrium models with a representative agent, the SDF represents marginal utility. The market price of disembodied shocks that drive the productivity of assets in place, λ_a, is unambiguously positive in traditional production-based asset pricing models (e.g., Jermann (1998)). Papanikolaou (2011) studies the pricing of aggregate embodied shocks in a two-sector general equilibrium model. Assuming recursive utility for the representative agent (Epstein and Zin (1989), Duffie and Epstein (1992)), Papanikolaou shows that the sign of the market price of embodied technology risk depends on preferences. While the impact of embodied shocks on current consumption is negative, as they incentivize a substitution from consumption to investment, recursive utility agents' marginal utility also depends on shocks to the future consumption path. Positive embodied shocks improve future consumption growth because of more intensive and more efficient capital formation. Therefore, the

[33] The partial equilibrium models of Kogan and Papanikolaou (2014) and Belo, Lin, and Bazdresch (2014) also use this form for the SDF.

market price of risk for disembodied shocks depends on how the representative agent's marginal utility is affected by shocks that improve the future growth prospects of the economy. A positive shock to the future consumption path lowers marginal utility in case the recursive utility agent prefers the early resolution of uncertainty, while it increases marginal utility otherwise. I discuss the quantitative implications of the market prices of risk for the present model in Section 3.5.

3.4 Firm problem

Each firm in the economy solves a standard equity value maximization problem assuming no financial leverage. The total costs of investment and hiring are given by

$$\Psi_t^T = i_t + \Psi_t^k + \Psi_t^n. \tag{18}$$

The firm pays dividend d_t, which is what remains from output after paying wages, investment expenditures, and adjustment costs, is given by

$$d_t = y_t - w_t^y \, l_t^y - w_t^o \, l_t^o - \Psi_t^T. \tag{19}$$

The cum-dividend value of the firm at time t is then given by

$$p_t = \max \, \mathbb{E}_t \left(\sum_{\tau=0}^{\infty} M_{t,t+\tau} \, d_{t+\tau} \right), \tag{20}$$

where the maximization problem is solved over $\{i_{t+\tau}, k_{t+\tau+1}, h_{t+\tau}^y, l_{t+\tau+1}^y, h_{t+\tau}^o, l_{t+\tau+1}^o\}_{\tau=0}^{\infty}$ subject to the law of motion for capital, both types of labor, and the stochastic processes. The set of state variables for the firm problem is given by $\Phi_t = \{u_t, a_t, \tilde{z}_t, z_t^a, k_t, l_t^y, l_t^o\}$. Finally, the gross equity return can be written as

$$R_{t+1} = \frac{p_{t+1}}{p_t - d_t}. \tag{21}$$

In the next section, I calibrate the model to inspect the mechanism behind the demographic dimension of hiring policy and expected returns.

3.5 Calibration

I calibrate the model at the monthly frequency and aggregate the results to annual frequency whenever the empirical counterpart of a moment is available at the annual frequency. I simulate 500 panels with 2,500 firms and a length of 50 years. Table 16 reports the parameter values and Table 17 reports the main average results from the model simulations. Data values correspond to the period from 1965 to 2015 unless otherwise stated. I set the shares of capital and labor, α_k and α_n, such that they imply a returns-to-scale parameter of 0.85 with shares of 0.35 and 0.65, respectively. I set the depreciation rate of capital to 0.01 to be in line with the depreciation rate of equipment in the data. The separation rate of employees is 0.03 to replicate the average aggregate labor separation rate in the data. I set the growth rate of TFP and IST shocks to the average growth of aggregate output in the data. There are wide-ranging estimates for the conditional volatility of aggregate IST shocks in the literature (see, e.g., Justiniano, Primiceri, and Tambalotti (2011), Schmitt-Grohé and Uribe (2011)). I set the annualized value to 0.08, which is within the estimated values in the literature, along with a conditional volatility of 0.035 for the aggregate TFP shock, which results in a volatility of 13% for aggregate dividend growth. Firm-specific productivity shocks are the source of heterogeneity in the present model. The unconditional average value ($\bar{z}$) of firm-specific IST is chosen such that $\tilde{z}_t$ has an average of 1. The average of (log) firm-specific productivity ($\bar{u}$) is a scaling variable, which I set to -3.4. The volatility and persistence parameters of firm-specific productivity shocks are calibrated jointly with adjustment cost parameters to generate realistic implications for the cross-section and time series of investment and hiring rates.

Parameters governing wage dynamics are chosen to replicate their data counterparts. The young-to-old ratio in average wages in the data is 0.61. I set the efficiency units of young and old employees, e_y and e_o, to replicate this number by setting the scale parameters for wages, $\bar{w}^y$ and $\bar{w}^o$, proportional to the efficiency units. I analyze the sensitivities of wages to aggregate shocks in the data using the KLEMS dataset. Table A.1 shows the loadings of average young and old wages per skilled employee to the TFP measure of Fernald (2014) and the IST measure of

Israelsen (2010). These two shocks have high explanatory power for one-, five-, and seven-year wage dynamics. Furthermore, young wages have a lower loading on the TFP shock and react more to the IST shock compared to the average wages of the old. Although wages are exogenously specified here, this is in line with the motivation of this model. As they play an important role in times of favorable shocks to technology embodied in new capital, young employees' compensation reacts more to the IST shock. Old employees have a more important role in existing operations, which is in line with wages that comove more with the productivity of assets in place. I target the annual average dynamics of wages in the calibration.[34] I set the scaling parameters for wages targeting the labor share in the data.[35] The labor share tends to be higher for value (high B/M) firms, which is a feature replicated by the model.

The adjustment cost parameters along with productivity processes are important for the moments related to investment and hiring. The model generates substantial time-series and cross-sectional volatility in hiring and investment rates but still undershoots these quantities in the data. This is due to the smooth form of adjustment cost functions, which lead to a lack of lumpiness in hiring and investment. I conjecture that one could improve on this dimension by adding a fixed component to the adjustment costs[36], but I keep the simpler adjustment cost specification and focus on the features of the model that help explain the novel evidence in Section 2. The parameter that determines the gains from having more young employees in the firm in the case of higher IST levels is c_z. It determines the average level and dynamics of the young-to-old ratio inside the firm. I set c_z to match the young-to-old ratio in the economy as well as ω for the high and low ω portfolios, which are the model counterparts of portfolios Y and O in the empirical analysis of Section 2. Note that, in the case of $c_z = 0$, firms find it optimal to hire old employees only, as there is no comparative advantage for the young and the old provide more efficiency units in production while their quantity is not costlier to adjust.

[34]The model assumes identical wages for all young and old employees in the economy. See Appendix C for a discussion of empirical cross-sectional variation in wages.

[35]I target the total wage bill in the calibration of the labor share including unskilled labor. Section 3.7 discusses how unskilled labor can be included in the present model.

[36]See Belo, Lin, and Bazdresch (2014) for an extensive analysis of fixed and variable adjustment costs in capital and labor.

3.6 Mechanism and asset pricing

Firms have differential exposure to aggregate TFP and IST shocks at every point in time depending on the history of firm-specific shocks that determines their current capital and labor quantities as well as the composition of their workforce. Because both shocks affect the SDF in (17), an approximate expression for the conditional risk premium of a firm can be written as

$$\mathbb{E}_t[r^i_{t+1} - r_f] \approx \beta^i_{a,t}\, \lambda_a\, \sigma_a + \beta^i_{z,t}\, \lambda_z\, \sigma_z, \tag{22}$$

where $\beta^i_{a,t}$ and $\beta^i_{z,t}$ are conditional exposures of firm i to TFP and IST shocks, respectively.

The central object of this paper is the adjustment of the workforce composition, namely when firms decide to increase or decrease the fraction of young employees represented by the variable ω. The benefits from having young employees, when the firm faces high embodied technology in new capital, is represented by high $\tilde{z}$. Therefore, the transition from low to high $\tilde{z}$ states correspond to periods of high ω as depicted in Figure 7, which shows the impulse response of quantities to a positive $\tilde{z}$ shock. Upon a positive shock to $\tilde{z}$, the firm increases the share of young employees rapidly. A transition to higher $\tilde{z}$ values also incentivizes investment because capital goods are effectively cheaper in this case. However, investment is initially low and spikes about one year after the positive shock to $\tilde{z}$, namely once the firm approaches the desired share of young employees in the workforce. At the time of the investment spike, ω is still positive; hence, there is still room for a higher share of young employees inside the firm. After two years, investment starts to drop once the $\tilde{z}$ shock is mean-reverting, and ω goes even below zero because the firm approaches the new higher level of capital and has more assets in place. Experienced workers are more productive in working with assets in place.[37]

A high value for $\tilde{z}$ lowers the replacement cost of capital (k/z) and increases the share of growth opportunities in the firm value. The exposure of growth opportunities to aggregate IST shocks is particularly high in times of high investment, and this exposure is amplified by adjustment costs that have not yet lowered fully through the adjustment of the labor composition. The YMO

[37]See Appendix B for a discussion of the forward-looking nature of ω, and the backward looking information in the share yof young employees in the workforce. Table 19 shows that the model replicates this feature of the data.

portfolio return in the model, which is long in high ω firms and short in low ω firms, has a high exposure to aggregate IST shocks. Therefore, a positive value for the market price of aggregate IST shocks (λ_z) helps explain the high average returns to the YMO strategy.

The primary focus of models explaining the cross-section of expected stock returns, is the value premium. The market-to-book ratio, which is the defining variable of the value premium, can be defined as $\frac{p}{k/z}$ in the model where k/z is the replacement cost of capital. A positive shock to $\tilde{z}$ lowers the replacement cost of capital, shifting the firm toward being categorized as a growth firm. Growth opportunities become a higher share of firm value, making growth firms more exposed to aggregate IST shocks.

A recent strand of literature explains the value premium using this differential impact of IST shocks on value and growth firms, and attaching a negative market price of risk to IST shocks. As discussed in Section 3.3, Papanikolaou (2011) achieves this in general equilibrium assuming a preference for the late resolution of uncertainty for the representative agent.[38] Kogan and Papanikolaou (2013) and Kogan and Papanikolaou (2014) study partial equilibrium models like the one described in the current paper and assume a negative price of risk for IST shocks explicitly.[39] These papers also provide evidence that growth firms are indeed more exposed to proxies of IST shocks, as also shown in Section 2.5.1. In recent empirical work, Garlappi and Song (2016) argue that measurements of exposures to IST shocks are highly dependent on the sample period used and the choice of test assets.

Another way of achieving the value premium within the neoclassical model of the firm is operating leverage. Zhang (2005) shows that capital adjustment costs give rise to the value premium and can be amplified by costly reversibility as in Abel and Eberly (1996), namely that downward adjustment of capital is costlier than expanding capital. In more recent work, Favilukis

[38]Other general equilibrium mechanisms with a similar pricing argument are Gârleanu, Kogan, and Panageas (2012), who argue that growth stocks hedge existing agents against future negative shocks to their human capital caused by innovation that benefits younger generations, and Kogan, Papanikolaou, and Stoffman (2016), who construct a model with incomplete markets and an unequal distribution of rents from innovation. Although not modeled as IST shocks, other papers argue that innovation lowers the marginal utility of the representative agent because of its long-run benefits, e.g., Kung and Schmid (2015).

[39]Belo, Lin, and Bazdresch (2014) also uses this approach in seeking an explanation for the gross hiring spread, namely that firms with low hiring rates have higher expected returns in the cross-section.

and Lin (2015) show the impact of wage rigidity on the aggregate market and the value premium. These models feature mechanisms that make the costs of the firm less procyclical than revenue, which amplifies the procyclicality of cash flows, increasing value firms' exposure to aggregate TFP shocks.[40]

The discussion above suggests that high positive values for λ_a help replicate the value premium, while there is a tension in the explanation of young-to-old spread and the value premium based on λ_z. While a positive value for λ_z can replicate the YMO spread, the exposure to embodies shocks helps explain the value premium with negative values of λ_z. A positive average YMO spread along with a positive value premium can be achieved by the choice of a positive λ_z, and a positive and high λ_a such that the impact of TFP shocks dominates the value premium. I confirm this by choosing values for λ_a and λ_z to match the average market excess return, stock market volatility, the average YMO spread, and the value premium.[41] The positive YMO spread is almost entirely compensation for the risk associated with IST shocks. The market price of TFP shocks is large enough to generate a value premium that is not overturned by the low exposure of value firms to IST shocks. The opposite exposures of the YMO and HML spreads to aggregate shocks gives rise to a negative correlation between the two, just as in the data. Finally, the model also generates a return spread between low and high hiring firms. The hiring return spread has a correlation of 89% with value minus growth in the model compared to 53% in the data.

Two mechanisms for operating leverage are embedded in the present model. Column 2 of Table 18 reports results from a calibration where the wage level parameters $\bar{w}^y$ and $\bar{w}^o$ are set to half of the values in the baseline calibration. In this case, the wage share of output is low substantially lowering the operating leverage effect from wage costs. This causes a substantial drop in the value premium. Column (4) of Table 18 reports results from the model with $c_z = 0$, which shuts down the dependence of capital adjustment costs on the composition of the workforce. Firms exclusively

[40]Specifically, adjustment costs prevent the firm from adjusting capital rapidly upon productivity shocks. Costly reversibility burdens the firm with unproductive capital in times of low productivity, as disinvestment is particularly costly. Finally, wage rigidity leads to labor costs that do not decrease proportional to productivity, making firm cash flows riskier.

[41]Specifically, I minimize a weighted sum of squared deviations of model values from data for these four moments, and search over integer values for λ_a and λ_z. All return moments have unit weight, while the weight of stock market volatility is one half.

employ old employees in this case, because an old employee has higher efficiency units in production while having the same adjustment cost. Therefore, it is more effective to use only old employees leading to a corner solution that the firm employs no young employees. The dependence of capital adjustment costs on workforce composition also induces an asymmetry in capital adjustment costs. Times of high investment tend to be times of lower than average adjustment costs (because $c_z < 0$) while low investment is usually associated with high adjustment costs. The average value of Φ_t^z is - 0.41 in periods of positive investment while it is 0.24 in times of disinvestment. As seen in Table 18, in the case of $c_z = 0$ the value premium drops substantially in this case as well. Value firms tend to have low firm-specific productivity, u. Therefore, they try to fire workers and disinvest, yet costly adjustment prevents them from making rapid adjustments at the extensive margin. At the same time, low values for $\tilde{z}$ imply a high replacement cost of capital, which is also a feature of value firms. Hence, value firms are expected to have positive exposure to aggregate TFP shocks and negative exposure to IST shocks. Table 17 shows that the exposure of returns to aggregate shocks is in line with the empirical evidence discussed in Section 2.5.1.

Finally, the momentum effect in the model arises due to the positive exposure of winners to IST shocks as shown in Table 17. Upon the arrival of a positive firm-specific IST shock, the firm starts adjusting the workforce toward young employees and the investment spike exhibits a slow and persistent pattern implying returns that are highly exposed to aggregate IST shocks.

3.7 Extensions

The calibration of the baseline model in Section 3.5 splits the workforce into demographic groups only, but does not consider the role of skilled and unskilled labor separately. However, part of the wage bill of firms is naturally paid to unskilled workers, they are thus represented in the labor share. In recent work, Belo, Lin, Li, and Zhao (2016) show that the hiring return spread documented in Belo, Lin, and Bazdresch (2014) is largely driven by industries that have a high share of skilled labor in the workforce. They argue that the hiring process for skilled employees is costlier, resulting in a larger association of hiring with asset prices through the adjustment cost channel. Appendix F illustrates an extension of the baseline model featuring unskilled labor in production. I assume that unskilled labor can be chosen every period and the hiring process does not involve adjustment costs unlike skilled labor consistent with the evidence in Belo, Lin, Li, and Zhao (2016). This approach does not increase the computational burden of the model because the number of endogenous state variables stays the same as in the baseline model. I calibrate this version of the model, as discussed in Appendix F, by targeting the total labor share of output. The asset pricing implications are largely unaffected. The value premium and the gross hiring spread are slightly lower due to the lower quantity of labor adjustment costs, and the time-series and cross-sectional volatilities of the hiring rate are lower in this version of the model. However, the young-minus-old hiring spread of the skilled workforce is still large which is the main objective of this paper.

The baseline model assumes that a young employee is less productive with all assets in place compared to an old employee. While this captures the value of experience in production, it may be counterfactual in the special case that most of assets in place have been installed recently. One can think of the possibility that a firm that has a high share of recently installed capital may want to hire younger employees because they may be more proficient in production with young capital. Lin, Palazzo, and Yang (2016) group firms by the average age of physical capital and find that the capital of the lowest decile portfolio has an average age of 9.5 quarters while it reaches 39 quarters for the highest decile. Hence, there is not a large number of firms with a high share of very recently installed capital, say, within the last year. Another dimension that the baseline model does not feature is that employees may become experienced inside the firm. In the current setup, however, the channel to increase the quantity of old labor is hiring from outside of the firm. To address these concerns, I consider a constant transition rate from the young to the old workforce of the firm by modifying the laws of motion for number of employees as follows:

$$l_{t+1}^{y} = (1 - s)\, l_t^{y} - s_y l_t^{y} + h_t^{y}, \tag{23}$$

and

$$l_{t+1}^{o} = (1 - s)\, l_t^{o} + s_y l_t^{y} + h_t^{o}, \tag{24}$$

where s_y is the fraction of young employees that joins the old workforce while staying inside the firm. In this case, a young employee does not necessarily remain less productive with existing capital. By the time the installation of capital due to a favorable firm-specific IST shock is complete, there is a probability that the employee switches to the old workforce and contributes to production with a high level of efficiency units. Table A.3 reports results by setting $s_y = 0.05$ and shows that this additional feature has no significant effect on main results.

Finally, the empirical evidence in Section 2 is at the industry level while the model is simulated at the firm level. As $\tilde{z}_t$ represents the technology embodied in new capital, and firms in the same industry are likely to use similar capital goods, one can group firms into industries where firms in the same industry have perfectly correlated $\tilde{z}_t$ processes. When the model is simulated with 25 industries containing 100 industries each, results are very close to the baseline specification. I do not report results from this simulation for brevity.

4 Conclusion

This paper shows that the demographic dimension of hiring activity is informative about the risks and opportunities that firms face, providing an ideal venue to study the interaction between demographics of the workforce and asset prices in an investment-based framework. Specifically, I document that a focus on young and skilled implies higher expected equity returns and is a leading indicator of medium-term period characterized by higher embodied technology in new capital for U.S. industries. Industries that shift their skilled workforce toward younger employees are more exposed to fluctuations in technological progress embodied in new capital which points to similar behavior to growth firms, while they have higher expected returns in contrast to growth firms. I provide a partial-equilibrium of the firm where demographic groups play differential roles in production and capital adjustment. The model offers an explanation for the implications of hiring demographics for equity returns, as well as for the interaction of this novel dimension of the data with established patterns in the cross-section of firms.

Appendix

A Data

This section describes data items that are used in the paper, and not described elsewhere in the text. The book-to-market ratio (B/M) is the ratio of book equity to market equity. Book equity is defined as total stockholders' equity plus deferred taxes and investment tax credit minus the book value of preferred stock from Compustat. Market equity is the number of shares outstanding multiplied by the share price from CRSP. Total employment of an industry is the sum of number of employees reported in Compustat. Employment growth (H/N) is the annual growth rate of total employment. I compare total employment growth numbers from Compustat to those from KLEMS and obtain similar results. Investment rate (I/K) is the ratio of capital expenditures to property, plant, and equipment from Compustat. Profitability (π/A) is the ratio of earnings before interest and taxes to total assets. Size is defined as the market equity value. The FF-3, FF-5, UMD factors and 49 industry returns are downloaded from Kenneth French's website. The q-factors are computed following Hou, Xue, and Zhang (2014). Wage data by demographic groups comes from the U.S. labor files of the KLEMS dataset. Returns differentials based on the gross hiring rate are computed following Belo, Lin, and Bazdresch (2014). The IST level of an industry is computed as the inverse of the relative price of capital services. Industry-level price indices for capital services are taken from the main U.S. files of the KLEMS data set. Investment for equipment, software, and R&D is computed as the some of investment in equipment and intellectual property products from industry-level NIPA accounts. For the labor share of a firm (Wages/Output), the ratio of wages to output of the corresponding industry from KLEMS is used. Industry level TFP data are from KLEMS as well. Age groups available in KLEMS are treated as equally-distributed when a cutoff does not lie at the available age cutoffs in the KLEMS data.

B Level versus change in demographic composition

This section provides evidence that the "level" of the demographic composition is backward looking, while the "change" is forward looking. Table A.5 shows that the level of the young-to-old ratio in the skilled workforce has no (or, negative, if anything) predictive power for future investment, while Table A.6 presents evidence that past investment activity predicts current levels of the young-to-old ratio, but not changes. This is consistent with the idea that young-hiring is concentrated at times when high investment is expected. Therefore, industries that have had high investment over the last three years have increased the share of young employees in the skilled workforce. Industries that plan to increase investments with high embodied productivity move toward a younger workforce. Therefore, changes in the demographic composition contain information about future investment activity that has not realized yet, and indicate ex-ante exposure to risks associated with these investments.

C Wage dynamics around demographic shifts

Is there any cross-sectional variation in wage growth across young and old hiring portfolios? Is young-hiring a cost-cutting measure? This section provides some descriptive statistics on wages before and after the demographic shifts observed at the time of portfolio formation. Table A.8 reports wage growth per employee and total wage growth for industries that are in the portfolios Y, M, and O. Portfolios are formed at time t. Industries do not differ significantly in wage growth per employee in the two years before portfolio formation, both for young and old employees. There is a dispersion in the portfolio formation year, where industries in portfolio Y have an average wage growth of 1.92% while it is 0.33% for industries in the old portfolio. This difference can be driven by the firms' desire to attract employees, and shrinks over the next three years after portfolio formation. Industries in portfolio O also experience high wage growth for old employees, on average, although their demand for old employees is high. This may be because the reduction in the number of old employees is driven by low-wage workers. The total wage bill growth of industries are also quite similar except for the portfolio formation year t. The high growth in the wage bill for young employees can be explained by the increase in their quantity, as the wage per employee effect is not very strong. Table A.9 further shows that industries are very similar in terms of their wage cost share, labor share, and operating leverage during, before, and after portfolio formation.[42] This suggests that a focus of hiring activity on the young is not merely a cost measure that firms take.

D Cash-flow predictability

The argument developed in this paper is that, at the time the dispersion in demographic shifts is observed, future investment plans are priced in the stock market, and the risk premium associated with risks in future investment gives rise to a cross-sectional dispersion in expected returns. Bansal, Dittmar, and Lundblad (2005) show that value and momentum can be tracked down to cash-flow betas. I investigate the sensitivity of future portfolio cash-flows to aggregate TFP and IST shocks. Tables A.13 and A.14 show that 1-year and, especially, 3-year dividend growth of firms in portfolio Y have significantly higher positive exposure to IST shocks. This is consistent with the empirical results based on portfolio returns: differences in the future cash-flow performance of young and old hiring industries are well predicted by past realizations of past productivity shocks in new vintages of capital. This supports that young-hiring portfolio rely heavily on the productivity embodied in new capital. If new capital turns out more productive, these industries can build more productive capital per unit investment expenditure, and this is reflected in future cash-flows.

The cash-flow exposure results also shed light on the fundamental relation between the young-old hiring spread, value-growth, and industry momentum. Future cash-flows of winner industries are also more exposed to IST shocks, while value firm cash-flows are more exposed to TFP shocks. This is consistent with the comovement of these three returns, and their comovement with aggregate shocks discussed in Section 2.5.1.

[42] I also computed the distribution of wage cost indicators, and their average 5% and 95% values are very close, and are not reported for brevity.

E Vintage capital and IST

This section shows an isomorphism between the baseline model with investment-specific technology and a model with vintage capital. Let k_τ^v be the quantity of capital installed at time τ (or, analogously, investment at τ) and z_τ be the productivity of the vintage where z_τ is set at τ and does not change. Assuming that capital depreciates at rate δ, the effectively available capital at time t from capital installed at τ is given by

$$z_\tau(1-\delta)^{t-(\tau+1)}k_\tau^v, \tag{E.1}$$

where $t > \tau$. The total effective capital available to the firm is then given by

$$k_t = \sum_{\tau=-\infty}^{t-1} z_\tau(1-\delta)^{t-(\tau+1)}k_\tau^v, \tag{E.2}$$

which represents the remaining quantity from all past vintages of capital, after accounting for depreciation, multiplied by the vintage-specific productivity. As a result, the law of motion for effective capital is given by

$$k_{t+1} = (1-\delta)k_t + z_t k_\tau^v. \tag{E.3}$$

Because k_τ^v is equivalent to investment, the laws of motion in (3) and (E.3) are identical. Assuming that effective capital, k_t, enters the production in the same way as in (1), the model with IST entering capital accumulation directly, and the model with vintage-specific productivity are isomorphic.

F Unskilled labor

This section extends the baseline model to include unskilled labor in production. The production function in this case is given by

$$\tilde{y}_t = u_t a_t k_t^{\alpha_k} n_t^{\alpha_n} n_{u,t}^{\alpha_u}, \tag{F.1}$$

where the inputs are defined as in (1), n_t is skilled labor, and $n_{u,t}$ is unskilled labor input. $n_{u,t}$ is given by $e_u l_t^u$ where e_u denotes the efficiency units of an unskilled employee, and l_t^u is the quantity of unskilled labor. I assume that unskilled labor is freely adjustable every period. Therefore, the choice of the quantity of unskilled labor is a static problem. Let w_t^u denote the wage rate of an unskilled employee. The static problem of the is then given by

$$\max_{l_t^u} u_t a_t k_t^{\alpha_k} n_t^{\alpha_n} n_{u,t}^{\alpha_u} - w_t^u l_t^u. \tag{F.2}$$

The first order condition of this problem implies that α_u is the share of output that is paid to unskilled employees as wage: $\alpha_u \tilde{y}_t = w_t^u l_t^u$. As a result, the maximand of (F.2) is $(1 - \alpha_u)\tilde{y}_t$. Because k_t and n_t are determined in period $t-1$, the optimal quantity of unskilled labor can be computed as $n_{u,t} = \left(\frac{\alpha_u \bar{y}_t}{w_t^u}\right)^{\frac{1}{1-\alpha_u}}$ where $\bar{y}_t = u_t a_t k_t^{\alpha_k} n_t^{\alpha_n} e_u^{\alpha_u}$. I specify the wage rate for unskilled employees as $w_t^u = \bar{w}^u \exp(\tau_a^u \Delta \log(a_t))$. I set the additional parameters to $e_u = 0.5$, $\bar{w}^u = 0.015 e_u$, $\tau_a^u = 1$, $\alpha_u = 0.23$, and set $\alpha_n = 0.23$ to account for the addition of another component for labor. I keep the remaining model assumptions and parameters values same as in the baseline case. Table $A.2$ reports the results.

G Computation

In the model, output y_t, components of labor l_{t+1}^y and l_{t+1}^o, investment i, adjustment costs Φ_t^T, dividends d_t, and firm value p_t follow at the same rate at the balanced growth rate. Let $\tilde{a}_t$ denote the trend variable characterizing the growth path such that the variables above are stationary when normalized by $\tilde{a}_t$, where $\tilde{a}_t = a_t^{\frac{1}{1-\alpha_k-\alpha_n}} (z_t^a)^{\frac{\alpha_k}{1-\alpha_k-\alpha_n}}$. Capital grows at a higher rate due to investment-specific technological progress where the replacement cost of capital k_{t+1}/z_t follows the same growth path as the variables listed above. I solve the firm's maximization problem using value function iteration. I discretize the state space for capital, young and old labor on a grid with non-binding lower and upper bounds. I discretize the aggregate TFP and IST shocks using Gaussian-Hermite quadrature. The firm-specific productivity processes are discretized using the method of Rouwenhorst (1995). I use cubic spline interpolation between grid points to obtain the optimal policies.

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Table 1: Industries

1	Mining and quarrying
2	Food products, beverages, and tobacco
3	Textiles, textile products, leather, and footwear
4	Wood and products of wood and cork
5	Pulp, paper, paper products, printing and publishing
6	Coke, refined petroleum products, and nuclear fuel
7	Chemicals and chemical products
8	Rubber and plastics products
9	Other non-metallic mineral products
10	Basic metals and fabricated metal products
11	Machinery
12	Electrical and optical equipment
13	Transport equipment
14	Other manufacturing
15	Electricity gas and water supply
16	Construction
17	Wholesale trade
18	Sale and maintenance of motor vehicles, retail sale of fuel
19	Retail trade
20	Accomodation and food services
21	Transport and storage
22	Post and telecommunications
23	Business services
24	Healthcare
25	Personal services
26	Financial activities
27	Real estate activities

Notes: Table lists the industries in the KLEMS data set that are used in this paper.

Table 2: Portfolio Characteristics

	Y	M	O
ω	0.05	0.00	-0.06
$\log(l_t^y/l_{t-1}^y)$	0.08	0.05	0.01
$\log(l_t^o/l_{t-1}^o)$	0.03	0.05	0.06
l_t^y/l_t^o	0.18	0.16	0.16
l_{t-1}^y/l_{t-1}^o	0.17	0.16	0.17
Market share	0.18	0.65	0.17
Book-to-market ratio			
Mean	0.65	0.61	0.72
Median	0.67	0.68	0.71
Employment growth			
Mean	0.05	0.04	0.04
Median	0.03	0.03	0.02
Investment rate			
Mean	0.19	0.18	0.17
Median	0.21	0.22	0.19
Profitability			
Mean	0.09	0.07	0.08
Median	0.08	0.07	0.07

Notes: Columns Y, M, and O refer to the young, medium, and old hiring portfolios, respectively. All statistics are computed in the cross-section of stocks every year from 1966 to 2015. Time-series averages are reported. ω is the log change in the ratio of young employees to old employees. Market share is the average market capitalization of stocks in the respective portfolio divided by the total market capitalization.

Table 3: Portfolio Returns

	Y	M	O	YMO
	Panel A: Excess returns			
$r - r_f$	9.17	5.08	4.52	4.64
	[3.73]	[2.21]	[1.79]	[3.09]
SR	0.52	0.32	0.26	0.40
	Panel B: CAPM			
α	3.44	-0.70	-0.74	4.18
	[2.73]	[-1.51]	[-0.49]	[2.78]
MKT	1.00	1.01	0.90	0.10
	[31.44]	[107.52]	[26.16]	[2.19]
R^2	0.81	0.97	0.75	0.02
	Panel C: Fama-French			
α	3.26	-0.45	-2.30	5.56
	[2.66]	[-1.01]	[-1.86]	[3.64]
MKT	0.99	1.00	0.95	0.04
	[34.46]	[121.52]	[28.91]	[0.71]
SMB	0.06	0.01	0.05	0.02
	[1.57]	[0.61]	[0.93]	[0.24]
HML	-0.12	-0.05	0.31	-0.30
	[-2.02]	[-2.57]	[4.60]	[-3.64]
R^2	0.81	0.97	0.78	0.08

Notes: Columns Y, M, and O refer to the young, medium, and old hiring portfolios, respectively. YMO is the difference between the returns of young and old hiring portfolios. Panel A reports portfolio excess returns and annualized Sharpe ratios (SR). Panel B reports results from CAPM time-series regressions. Panel C reports results from time-series regressions using the Fama and French (1993) 3-factor model. α is the regression intercept. Lines MKT, SMB, and HML report the coefficients on the corresponding factors. Data are monthly from January 1966 to December 2015. Returns and α's are multiplied by 1,200. t-statistics in brackets are based on Newey-West standard errors.

Table 4: Alternative Factor Models

	Y	M	O	YMO
	Panel A: q factors			
α	3.58	-0.08	-2.14	5.72
	[2.73]	[-0.12]	[-1.35]	[2.78]
MKT	1.01	1.00	0.94	0.07
	[32.94]	[93.86]	[28.71]	[1.33]
SMB	0.07	-0.01	0.05	0.02
	[1.53]	[-0.68]	[0.72]	[0.21]
INV	-0.08	-0.09	0.33	-0.29
	[-1.37]	[-1.63]	[2.55]	[-1.98]
PROF	0.09	-0.01	0.00	0.09
	[1.45]	[-0.44]	[0.03]	[0.78]
R^2	0.82	0.98	0.78	0.05
	Panel B: Fama-French 5 factors			
α	3.04	-0.28	-3.12	6.16
	[2.37]	[-0.56]	[-2.21]	[3.64]
MKT	1.00	0.99	0.97	0.03
	[35.82]	[117.52]	[30.19]	[0.51]
SMB	0.07	0.01	0.08	-0.01
	[1.36]	[0.61]	[1.58]	[-0.12]
HML	-0.09	-0.03	0.26	-0.28
	[-1.54]	[-1.43]	[3.56]	[-2.48]
INV	0.05	-0.05	0.10	-0.05
	[0.49]	[-1.64]	[1.11]	[-0.37]
PROF	0.02	-0.01	0.14	-0.12
	[0.21]	[-0.35]	[1.91]	[-1.10]
R^2	0.81	0.97	0.79	0.08

Notes: Columns Y, M, and O refer to the young, medium, and old hiring portfolios, respectively. YMO is the difference between the returns of young and old hiring portfolios. Panel A reports results from time-series regressions using the Hou, Xue, and Zhang (2014) 4-factor model. Panel B reports results from time-series regressions using the Fama and French (2015) 5-factor model. Lines MKT, SMB, HML, INV, and PROF report the coefficients on the corresponding factors. Data are monthly from January 1966 to December 2015. Returns and α's are multiplied by 1,200. t-statistics in brackets are based on Newey-West standard errors.

Table 5: Firm-Level Stock Return Predictability

	(1)	(2)	(3)	(4)	(5)	(6)
ω	0.14	0.15	0.15	0.16	0.14	0.16
	[4.11]	[4.24]	[4.20]	[4.43]	[4.13]	[4.64]
I/K		-0.14				-0.12
		[-5.22]				[-4.48]
H/N			-0.09			-0.08
			[-4.15]			[-3.38]
B/M				0.03		0.02
				[5.13]		[4.50]
M					-0.17	-0.13
					[-3.17]	[-3.02]
$\bar{R}^2$	0.15	0.16	0.15	0.15	0.14	0.17

Notes: Table reports results from pooled OLS regressions of annual stock returns on five different combinations of characteristics ω (difference between young and old hiring rate), I/K (investment rate), H/N (gross hiring rate), B/M (book-to-market ratio), M (log market cap). The independent variables are winsorized at the top and bottom 0.5 percentile resulting in 116,287 firm-year observations. Estimates of intercepts are not reported. Regressions include year and industry fixed effects. t-statistics are computed from standard errors clustered at the firm level.

Table 6: Double-Sorted Excess Portfolio Returns

	High	Med	Low	High - Low	α_{hl}	High	Med	Low	High - Low	α_{hl}
	Panel A: Book-to-market ratio					Panel B: Size				
Y	11.33	8.95	7.78	3.54	-0.51	8.95	12.08	10.64	-1.69	1.09
				[1.67]	[-0.32]				[-0.51]	[0.53]
M	8.80	5.99	4.84	3.96	-0.14	5.10	7.05	8.94	-3.48	-0.74
				[2.34]	[-0.14]				[-1.34]	[-0.47]
O	8.76	5.66	3.13	5.63	2.97	4.37	7.58	9.57	-5.19	-3.04
				[2.63]	[1.56]				[-1.92]	[-1.26]
YMO	2.57	3.28	4.66			4.58	4.55	1.07		
	[1.55]	[2.07]	[2.89]			[3.39]	[2.56]	[0.43]		
α_{ymo}	2.35	3.90	5.84			5.37	5.62	1.22		
	[1.15]	[2.18]	[3.44]			[3.61]	[2.44]	[0.42]		
	Panel C: Investment rate					Panel D: Employment growth				
Y	6.11	8.84	10.56	-4.45	-2.22	7.15	9.34	11.17	-4.02	-1.66
				[-1.58]	[-0.93]				[-2.10]	[-0.87]
M	4.09	5.79	6.97	-2.88	-0.87	4.33	5.14	7.71	-3.37	-1.51
				[-1.27]	[-0.57]				[-2.23]	[-1.36]
O	2.80	4.12	6.55	-3.75	-2.51	4.63	4.85	5.63	-1.00	0.08
				[-1.51]	[-1.24]				[-0.62]	[0.05]
YMO	3.31	4.72	4.01			2.52	4.48	5.54		
	[1.54]	[2.88]	[2.23]			[1.48]	[3.18]	[3.20]		
α_{ymo}	4.62	5.84	4.33			4.29	4.90	6.03		
	[1.75]	[3.40]	[2.16]			[2.23]	[3.27]	[3.03]		

Notes: Table reports excess returns from two-way double sorts. Rows Y, M, and O refer to the young, medium, and old hiring portfolios, respectively. YMO is the difference between the returns of young and old hiring portfolios. The computation of sorting variables from accounting data used to form portfolios High, Med, and Low, is described in Appendix A. Breakpoints for the accounting variable are 30^{th} and 70^{th} percentiles. α_{hl} is the FF-3 model alpha of the corresponding High - Low return. α_{ymo} is the FF-3 model alpha of the corresponding YMO return. Data are monthly from January 1966 to December 2015. Returns are value-weighted and multiplied by 1,200. t-statistics in brackets are based on Newey-West standard errors.

Table 7: Industries by Exposure to YMO

1	Computer software
2	Electronic equipment
3	Computers
4	Measuring & cont. equipment
5	Steel works
45	Defense
46	Plastic products
47	Personal services
48	Entertainment
49	Soda

Notes: Table lists five industries that have the highest and lowest coefficient on YMO in monthly time-series regressions of portfolio excess returns on YMO. 49 industry return series from Kenneth French's website are used. Data are monthly from January 1966 to December 2015.

Table 8: Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: YMO							
	5.41	4.44	3.96	3.48	3.71	4.08	3.96	4.24
	[2.30]	[2.39]	[2.60]	[2.08]	[1.96]	[2.20]	[2.33]	[2.68]
	Panel B: Fama-French 5 factor							
α	8.28	5.88	5.64	4.06	7.92	6.96	3.84	5.84
	[3.01]	[3.26]	[3.66]	[2.02]	[3.74]	[3.48]	[2.15]	[3.02]
MKT	0.04	-0.02	0.01	0.07	-0.11	-0.06	0.14	0.02
	[0.60]	[-0.29]	[0.23]	[1.31]	[-2.00]	[-1.29]	[2.69]	[0.42]
SMB	-0.11	0.06	0.01	0.03	-0.04	0.15	0.12	0.00
	[-1.02]	[0.66]	[0.11]	[0.46]	[-0.71]	[2.68]	[1.45]	[0.01]
HML	-0.42	-0.20	-0.36	-0.27	-0.33	-0.26	-0.28	-0.27
	[-2.47]	[-1.61]	[-3.59]	[-2.63]	[-2.81]	[-2.46]	[-2.45]	[-2.34]
INV	0.05	-0.11	0.00	0.05	-0.46	-0.41	0.03	-0.05
	[0.23]	[-0.72]	[0.02]	[0.37]	[-2.24]	[-0.66]	[0.31]	[-0.45]
PROF	-0.23	-0.14	-0.10	-0.06	-0.40	-0.11	0.02	-0.10
	[-0.99]	[-1.17]	[-1.04]	[-0.58]	[-2.68]	[-0.66]	[0.10]	[-0.87]

Notes: Panel A reports YMO, the difference between the returns of young and old hiring portfolios, for seven alternative empirical settings:

(1) uses data from January 1966 to December 1989,
(2) uses data from January 1990 to December 2015,
(3) reports the result excluding financial and real estate industries,
(4) reports the result excluding all firms reporting positive R&D expenditures in Compustat,
(5) reports results with an age threshold of 35 between young and old,
(6) reports results with equal-weighting,
(7) reports results using a time-varying definition of skill.
(8) reports results using industry-specific age-cutoffs using the age at the 20th percentile of an industry in the previous year.
Panel B reports results from time-series regressions of YMO using the Fama and French (2015) 5-factor model. t-statistics in brackets are based on Newey-West standard errors.

Table 9: Five Portfolio Returns

	Y	2	3	4	O	YMO
			Panel A: Excess returns			
$r - r_f$	9.17	5.90	5.77	5.03	4.52	4.64
	[3.73]	[2.04]	[2.32]	[1.95]	[1.79]	[3.09]
			Panel B: CAPM			
α	3.44	-0.20	-0.19	-0.36	-0.74	4.18
	[2.73]	[-0.15]	[-0.23]	[-0.31]	[-0.49]	[2.78]
MKT	1.00	1.07	1.04	0.94	0.90	0.10
	[31.44]	[34.68]	[39.91]	[27.09]	[26.16]	[2.19]
R^2	0.81	0.84	0.90	0.78	0.75	0.02
			Panel C: Fama-French			
α	3.26	0.34	-0.30	-0.14	-2.30	5.56
	[2.66]	[0.34]	[-0.37]	[-0.13]	[-1.86]	[3.64]
MKT	0.99	1.02	1.02	0.90	0.95	0.04
	[34.46]	[51.82]	[53.00]	[29.92]	[28.91]	[0.71]
SMB	0.06	0.10	0.01	0.12	0.05	0.02
	[1.57]	[2.87]	[0.38]	[2.52]	[0.93]	[0.24]
HML	-0.12	-0.15	-0.10	-0.09	0.31	-0.30
	[-2.02]	[-3.46]	[-1.96]	[-1.47]	[4.60]	[-3.64]
R^2	0.81	0.86	0.90	0.79	0.78	0.08

Notes: Columns Y, 2, 3, 4 and O refer to the portfolios with the highest to lowest value of ω. YMO is the difference between the returns of young and old hiring portfolios. Panel A reports portfolio excess returns. Panel B reports results from CAPM time-series regressions. Panel C reports results from time-series regressions using the Fama and French (1993) 3-factor model. Data are monthly from January 1965 to December 2015. Returns and α's are multiplied by 1,200. t-statistics in brackets are based on Newey-West standard errors.

Table 10: Annual Portfolio Returns

	Y	M	O	YMO
Panel A: Excess returns				
$r - r_f$	10.13	6.25	5.28	4.84
	[4.99]	[2.92]	[3.06]	[3.68]
Panel B: CAPM				
α	3.78	-0.25	-0.32	4.10
	[2.38]	[-0.39]	[-0.24]	[3.02]
MKT	1.01	1.03	0.89	0.12
	[12.05]	[30.58]	[9.59]	[0.83]
R^2	0.75	0.95	0.76	0.02
Panel C: Fama-French				
α	3.96	0.44	-2.58	6.53
	[2.44]	[0.71]	[-2.44]	[3.46]
MKT	0.99	0.99	0.95	0.03
	[11.83]	[37.16]	[18.38]	[0.30]
SMB	0.06	0.06	0.07	-0.01
	[0.58]	[2.06]	[1.03]	[-0.09]
HML	-0.05	-0.14	0.36	-0.42
	[-0.50]	[-2.79]	[4.48]	[-2.61]
R^2	0.75	0.96	0.84	0.12

Notes: Columns Y, M, and O refer to the young, medium, and old hiring portfolios, respectively. YMO is the difference between the returns of young and old hiring portfolios. Panel A reports portfolio excess returns. Panel B reports results from time-series regressions implied by the CAPM. Panel C reports results from time-series regressions using the Fama and French (1993) 3-factor model. Data are annual from 1966 to 2015. Returns and α's are multiplied by 1,200. t-statistics in brackets are based on Newey-West standard errors.

Table 11: Industry Momentum

Period	Sort	Low	2	3	4	High	High-Low	α_{capm}	α_{ff}	α_{mktymo}	α_{ymo}
Panel A: Fama-French 30 Industries											
1966-2015	6m-12m	4.05	5.71	6.53	7.92	8.53	4.48	3.43	5.13	2.28	2.78
							[2.87]	[2.40]	[3.51]	[1.36]	[1.85]
1966-1999	6m-12m	3.95	5.23	6.16	8.04	8.87	4.92	3.94	4.76	2.03	2.65
							[2.70]	[2.82]	[2.56]	[1.11]	[2.20]
1966-2015	2m-6m	4.90	6.95	7.43	6.66	7.11	2.21	3.23	5.62	3.10	2.19
							[1.68]	[1.99]	[2.56]	[2.12]	[1.73]
1966-1999	2m-6m	4.33	6.92	7.75	5.74	7.82	3.49	4.63	6.55	3.88	2.73
							[2.36]	[2.14]	[2.25]	[1.85]	[1.54]
Panel B: ISIC 27 Industries											
1966-2015	6m-12m	5.78	5.80	6.86	8.75	9.02	3.24	1.91	3.97	0.65	1.60
							[2.05]	[0.93]	[1.94]	[0.30]	[0.88]
1966-1999	6m-12m	4.59	4.97	6.31	9.47	10.20	5.60	3.98	4.91	2.02	3.22
							[2.36]	[1.59]	[1.64]	[0.82]	[1.42]
1966-2015	2m-6m	6.41	6.39	7.57	6.99	8.43	2.02	3.09	7.42	1.05	-0.18
							[0.96]	[1.83]	[2.20]	[0.50]	[-0.08]
1966-1999	2m-6m	6.33	5.45	7.38	6.49	9.44	3.10	4.08	8.63	1.06	-0.25
							[0.97]	[1.46]	[2.00]	[0.32]	[-0.08]

Notes: Table reports results for industry momentum. The “Period” column reports the sample period used. “Sort” is the period used to compute industry momentum: 6m-12m uses returns from 12-month to 6-month before portfolio formation. 2m-6m uses returns from 6-month to 2-month before portfolio formation as the sorting variable. The columns Low to High report excess returns of momentum portfolios from lowest to highest value for the corresponding momentum variable. High-Low is the average return from the strategy long in the highest and short in the lowest momentum portfolio. α_{capm} and α_{ff} are the intercepts from time-series regressions of the High-Low return based on CAPM and Fama and French (1993), respectively. α_{mktymo} is the intercept from the regression of the High-Low return on the market excess return and YMO. α_{ymo} is the intercept from the regression of the High-Low return on YMO. Data are annual and t-statistics in brackets are based on Newey-West standard errors.

Table 12: Macroeconomic Shocks

	YMO			HML			INDMOM		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Δa	-3.21	-3.45		3.97	4.84		-4.79	-5.84	
	[-1.46]	[-2.03]		[1.99]	[2.80]		[-2.01]	[-2.52]	
Δz	3.99			-1.18			2.66		
	[2.15]			[-0.65]			[1.92]		
R_m			-0.02			-1.28			0.97
			[-0.01]			[-0.86]			[0.57]
R_{imc}		1.65	1.57		-2.06	-1.87		1.67	1.49
		[4.20]	[3.59]		[-8.83]	[-6.60]		[11.75]	[8.44]
$\bar{R}^2$	0.07	0.27	0.19	0.03	0.46	0.37	0.08	0.39	0.24

Notes: Table reports results from OLS time series regressions of YMO, HML, and INDMOM returns on combinations of macroeconomic shocks. Δa is the growth of total factor productivity (TFP) from Fernald (2014). Δz is the growth of investment-specific technology (IST) from Israelsen (2010). R_m is the aggregate market excess return. R_{imc} is the return differential between investment good and consumption good producing sectors as in Papanikolaou (2011). Data are annual from 1966 to 2012. t-statistics in brackets are based on Newey-West standard errors. Regression intercepts are not reported.

Table 13: Demographic Shifts and Investment in Equipment, Software, and R&D

Panel A: Relation to future investment growth						
	$\Delta I_{t,t+1}$	$\Delta I_{t,t+1}$	$\Delta I_{t,t+3}$	$\Delta I_{t,t+3}$	$\Delta I_{t-1,t}$	$\Delta I_{t-1,t}$
ω_t	7.52	6.61	23.38	14.75	2.45	2.83
	[4.50]	[2.51]	[6.72]	[2.97]	[1.44]	[1.23]
R^2 in %	3.06	59.17	8.04	64.01	0.35	58.27
FE	N	Y	N	Y	N	Y

Panel B: Relation to future investment rate						
	I_{t+1}/K_t	I_{t+1}/K_t	$I_{t+1,t+3}/K_t$	$I_{t+1,t+3}/K_t$	I_t/K_{t-1}	I_t/K_{t-1}
ω_t	2.75	2.94	13.84	10.42	1.33	1.26
	[4.92]	[2.74]	[7.17]	[2.73]	[1.83]	[1.10]
R^2 in %	3.42	54.80	7.51	55.79	0.46	0.54
FE	N	Y	N	Y	N	Y

Notes: Table reports results from panel regressions using industry observations at the annual frequency from 1965 to 2014. FE is fixed effects. Columns with N are without, Y with industry and year fixed effects. t-statistics are based on standard errors clustered at the industry level. All coefficients are multiplied by 100. ω_t normalized to have unit standard deviation among all industry-year observations. ΔI is investment growth rate in equipment, software, and R&D. I/K is the quantity of investment divided by the quantity of fixed assets. $I_{t+1,t+3}$ is total investment from year $t+1$ to $t+3$. The left-hand variable is at the top of each column, the right-hand variable is ω_t where $\omega_t = \log(l_t^y/l_{t-1}^y) - \log(l_t^o/l_{t-1}^o)$. Regressions use 1,323 observations.

Table 14: Demographic Shifts and Investment in Structures

Panel A: Relation to future investment growth						
	$\Delta I_{t,t+1}$	$\Delta I_{t,t+1}$	$\Delta I_{t,t+3}$	$\Delta I_{t,t+3}$	$\Delta I_{t-1,t}$	$\Delta I_{t-1,t}$
ω_t	2.14	1.78	9.31	1.26	-0.25	-1.48
	[1.41]	[0.27]	[2.69]	[0.16]	[-0.14]	[-0.43]
R^2 in %	0.02	68.51	0.30	58.62	0.00	70.32
FE	N	Y	N	Y	N	Y
Panel B: Relation to future investment rate						
	I_{t+1}/K_t	I_{t+1}/K_t	$I_{t+1,t+3}/K_t$	$I_{t+1,t+3}/K_t$	I_t/K_{t-1}	I_t/K_{t-1}
ω_t	2.45	0.62	9.72	2.26	1.67	0.40
	[2.37]	[1.28]	[3.90]	[1.60]	[2.05]	[0.72]
R^2 in %	2.91	73.38	4.77	76.41	0.66	72.69
FE	N	Y	N	Y	N	Y

Notes: Table reports results from panel regressions using industry observations at the annual frequency from 1965 to 2014. FE is fixed effects. Columns with N are without, Y with industry and year fixed effects. t-statistics are based on standard errors clustered at the industry level. All coefficients are multiplied by 100. ω_t normalized to have unit standard deviation. ΔI is investment growth rate in structures. I/K is the quantity of investment divided by the quantity of fixed assets. $I_{t+1,t+3}$ is total investment from year $t+1$ to $t+3$. The left-hand variable is at the top of each column, the right-hand variable is ω_t where $\omega_t = \log(l_t^y/l_{t-1}^y) - \log(l_t^o/l_{t-1}^o)$. Regressions use 1,323 observations.

Table 15: Future Investment and Demographic Shifts

	ω_t			
$\Delta I_{t,t+3}$	0.21	0.13	0.22	0.12
	[3.50]	[1.84]	[3.19]	[1.62]
$z_{t,t+3}$			0.16	-0.02
			[2.42]	[-0.78]
$z_{t,t+3} \cdot \Delta I_{t,t+3}$		0.15		0.15
		[4.86]		[6.42]
R^2	0.64	0.66	0.65	0.67
FE	Y	Y	Y	Y

Notes: Table reports results from four regressions of ω_t on investment growth over the next three years ($\Delta I_{t,t+3}$), industry level IST over the three years ($z_{t,t+3}$), and an interaction term. Regressions include year and industry fixed effects. t-statistics are based on standard errors clustered at the industry level. ω_t, $z_{t,t+3}$, and $\Delta I_{t,t+3}$ are normalized to have unit standard deviation across all industry-year observations. ΔI is investment growth rate in equipment, software, and R& D. All regressions use 1,323 industry-year observations from 1966 to 2014.

Table 16: Parameters for Benchmark Calibration

α_k	0.2975	δ	0.01	μ_a	0.01/12
α_n	0.5525	s	0.03	σ_a	$0.035/\sqrt{12}$
e_y	0.77	c_n	4	μ_z	0.01/12
e_o	1.23	c_k	6	σ_z	$0.08/\sqrt{12}$
$\bar{w}^y$	0.015 e_y	c_z	-60	ρ_u	0.98
$\bar{w}^o$	0.015 e_o	r_f	0.0165/12	σ_u	0.05
τ_a^y	0.37	λ_a	25	ρ_z	0.98
τ_z^y	0.28	λ_z	5	$\sigma_{\tilde{z}}$	0.01
τ_a^o	0.68				
τ_z^o	-0.11				

Notes: α_k and α_n are the capital and labor share parameters in the production function. e_y and e_o ar the efficiency units of young and old employees. δ is the capital depreciation rate. s is the labor separation rate. $\bar{w}^y$ and $\bar{w}^o$ are level parameters for wages of young and old employees. τ_a^y, τ_z^y, τ_a^o, and τ_z^o are the parameters governing young and old wages to shocks to a and z^a. c_n and c_k are parameters of labor and capital adjustment costs. c_z is the parameter governing the impact of labor composition on capital adjustment costs. μ_a and μ_z are growth rates, σ_a and σ_z are conditional volatilities of aggregate productivity processes a and z^a. ρ_u and ρ_z are the persistence parameters, and σ_u and $\sigma_{\tilde{z}}$ are the conditional volatilities of firm-specific productivity processes u and $\tilde{z}$.

Table 17: Model Moments

Panel A: Real moments

	Data	Model		Data	Model		Data	Model
$\sigma(\Delta D_t)$	0.14	0.13	β_a^y	0.37	0.37	$\sigma(h/n)$ XS	0.26	0.13
$\mathbb{E}\left[w_t^y/w_y^o\right]$	0.61	0.61	β_z^y	0.28	0.28	$\sigma(h/n)$ TS	0.23	0.16
Wages/Output (value)	0.68	0.74	β_a^o	0.68	0.67	$\sigma(i/k)$ XS	0.21	0.17
Wages/Output (growth)	0.53	0.43	β_z^o	-0.11	-0.11	$\sigma(i/k)$ TS	0.23	0.18
Ψ_t^n/W_t^h	0.69	0.61	$\mathbb{E}[l_t^y/l_t^o]$	0.16	0.15	$\mathbb{E}[\omega]$ young	1.05	1.07
						$\mathbb{E}[\omega]$ old	0.94	0.96

Panel B: Asset pricing moments

	Data	Model		Data	Model
$\mathbb{E}\left[r_m - r_f\right]$	6.29	5.01	β_a^{yo}	-3.21	-1.93
$\sigma(r_m)$	18.10	14.46	β_z^{yo}	3.99	5.42
$\mathbb{E}\left[r_y - r_o\right]$	4.64	5.01	β_a^{vg}	3.97	5.95
$\mathbb{E}\left[r_v - r_g\right]$	6.04	5.17	β_z^{vg}	-1.18	-1.21
$\mathbb{E}\left[r_w - r_l\right]$	5.61	4.23	β_a^{wl}	-5.84	-2.18
$\mathbb{E}\left[r_e - r_c\right]$	4.48	3.60	β_z^{wl}	2.66	4.78
$corr(r_v - r_g, r_y - r_o)$	-0.28	-0.22			

Notes: $\sigma(\Delta D_t)$ is the annual volatility of aggregate dividends. $\mathbb{E}\left[w_t^y/w_y^o\right]$ is the average ratio of wages for young to old employees. Wages/Sales (value) and Wages/Sales (growth) is the average ratio of the wage bill to sales for the firms highest and lowest decile book-to-market deciles. Ψ_t^n/W_t^h is the average ratio of labor adjustment costs to the quarterly wages of new hires. β_a^y, β_z^y, β_a^o, β_z^y are defined in Table A.1. $\mathbb{E}[l_t^y/l_t^o]$ is the average ratio of the number of young to old employees in the economy. $\sigma(h/n)$ XS and $\sigma(i/k)$ XS are the time series averages of the cross-sectional volatility in annual hiring and investment rates. $\mathbb{E}[\omega]$ young and $\mathbb{E}[\omega]$ old are the average values of ω for portfolios Y and O. $\mathbb{E}\left[r_m - r_f\right]$ is the annual aggregate market excess return in %. $\sigma(r_m)$ is the annual aggregate stock market volatility in %. $\mathbb{E}\left[r_y - r_o\right]$ is the average return differential in % between extreme quintile portfolios sorted on ω representing the YMO spread (young minus old). $\mathbb{E}\left[r_v - r_g\right]$ is the average return differential in % between extreme decile portfolios sorted on book-to-market ratio representing the value premium (value minus growth). $\mathbb{E}\left[r_w - r_l\right]$ is the average return differential in % between extreme quintile portfolios sorted on momentum (winners minus losers). $\mathbb{E}\left[r_e - r_c\right]$ is the average return differential in % between extreme decile portfolios sorted on gross hiring rate (expanding minus contracting). $corr(r_v - r_g, r_y - r_o)$ is the correlation between the monthly returns $r_v - r_g$ and $r_y - r_o$. β_a^{yo} and β_z^{yo} are the loadings of $r_y - r_o$ in annual contemporaneous regressions on Δa and Δz^a. β_a^{vg} and β_z^{vg} are the loadings of $r_v - r_g$ in annual contemporaneous regressions on Δa and Δz^a. β_a^{wl} and β_z^{wl} are the loadings of $r_w - r_l$ in annual contemporaneous regressions on Δa and Δz^a. β's are computed using normalized right-hand variables.

Table 18: Alternative Model Specifications

	Data	Baseline	Low wage	$c_z = 0$
$\mathbb{E}[r_m - r_f]$	6.29	5.01	3.12	4.15
$\sigma(r_m)$	18.10	14.46	7.67	8.12
$\mathbb{E}[r_y - r_o]$	4.64	5.01	4.15	0.00
$\mathbb{E}[r_v - r_g]$	6.04	5.17	1.42	1.21

Notes: $\mathbb{E}[r_m - r_f]$ is the annual aggregate market excess return in %. $\sigma(r_m)$ is the annual aggregate stock market volatility in %. $\mathbb{E}[r_y - r_o]$ is the average return differential in % between extreme quintile portfolios sorted on ω representing the YMO spread. $\mathbb{E}[r_v - r_g]$ is the average return differential in % between extreme decile portfolios sorted on book-to-market ratio representing the value premium. Low wage is a calibration with lower wages. $c_z = 0$ shuts off the impact of labor composition on capital adjustment costs.

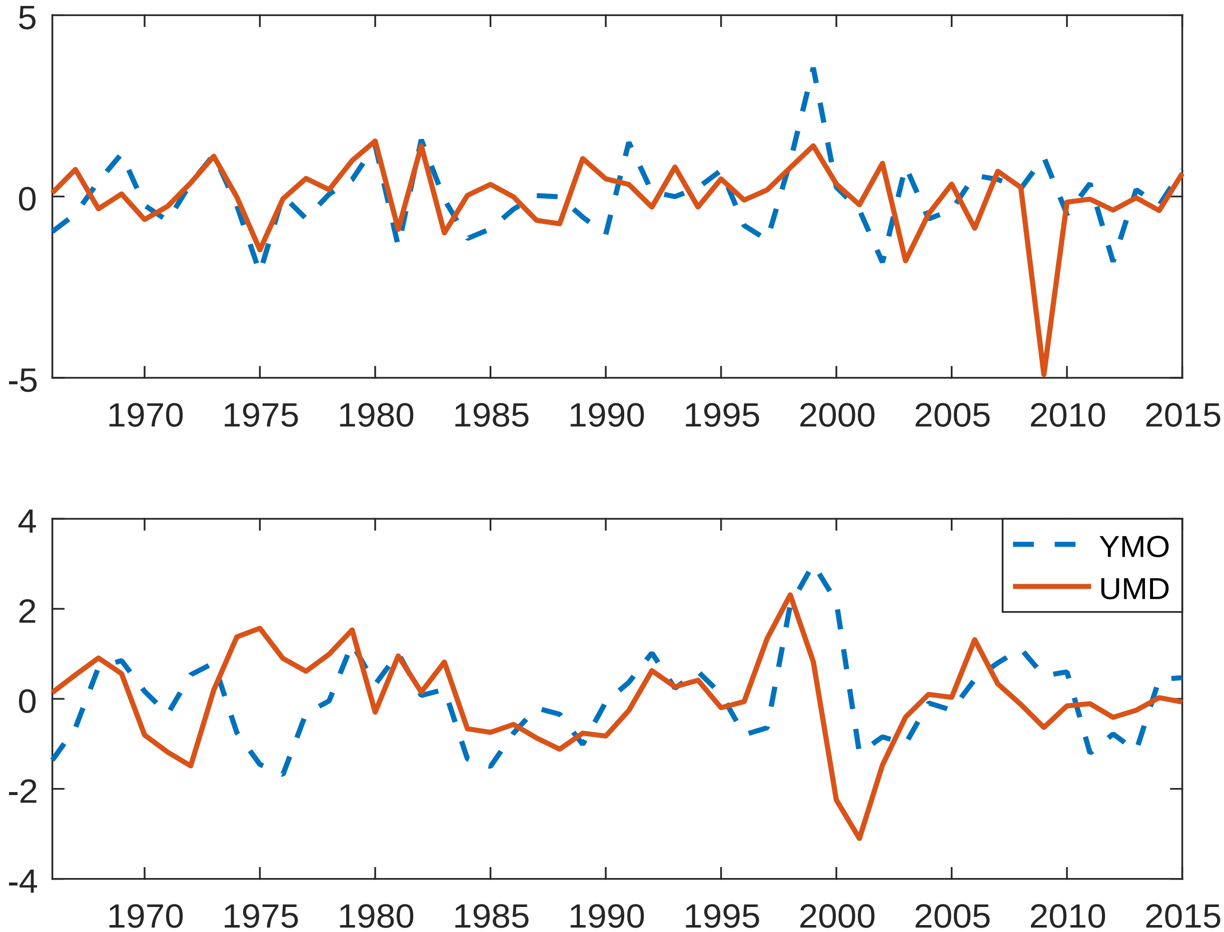
Table 19: Demographics and Investment in the Model

Panel A: Predicting demographics				
	$\Delta I_{t,t+1}$	$\Delta I_{t,t+1}$	$\Delta I_{t,t+3}$	$\Delta I_{t,t+3}$
		Data		
ω_t	6.61		14.75	
	[2.51]		[2.97]	
$\log(l_t^y/l_t^o)$		-1.66		-4.46
		[-1.03]		[-1.66]
		Model		
ω_t	7.84		16.32	
	[6.12]		[7.14]	
$\log(l_t^y/l_t^o)$		1.02		0.24
		[1.31]		[0.68]

Panel B: Predicting investment growth				
	ω_{t+1}	ω_{t+1}	$\log(l_t^y/l_t^o)$	$\log(l_t^y/l_t^o)$
		Data		
$\Delta I_{t-1,t}$	0.08		0.72	
	[1.65]		[7.10]	
$\Delta I_{t-3,t}$		0.03		0.66
		[0.60]		[8.40]
		Model		
$\Delta I_{t-1,t}$	0.23		1.23	
	[0.14]		[4.54]	
$\Delta I_{t-3,t}$		-0.04		0.48
		[-0.45]		[6.41]

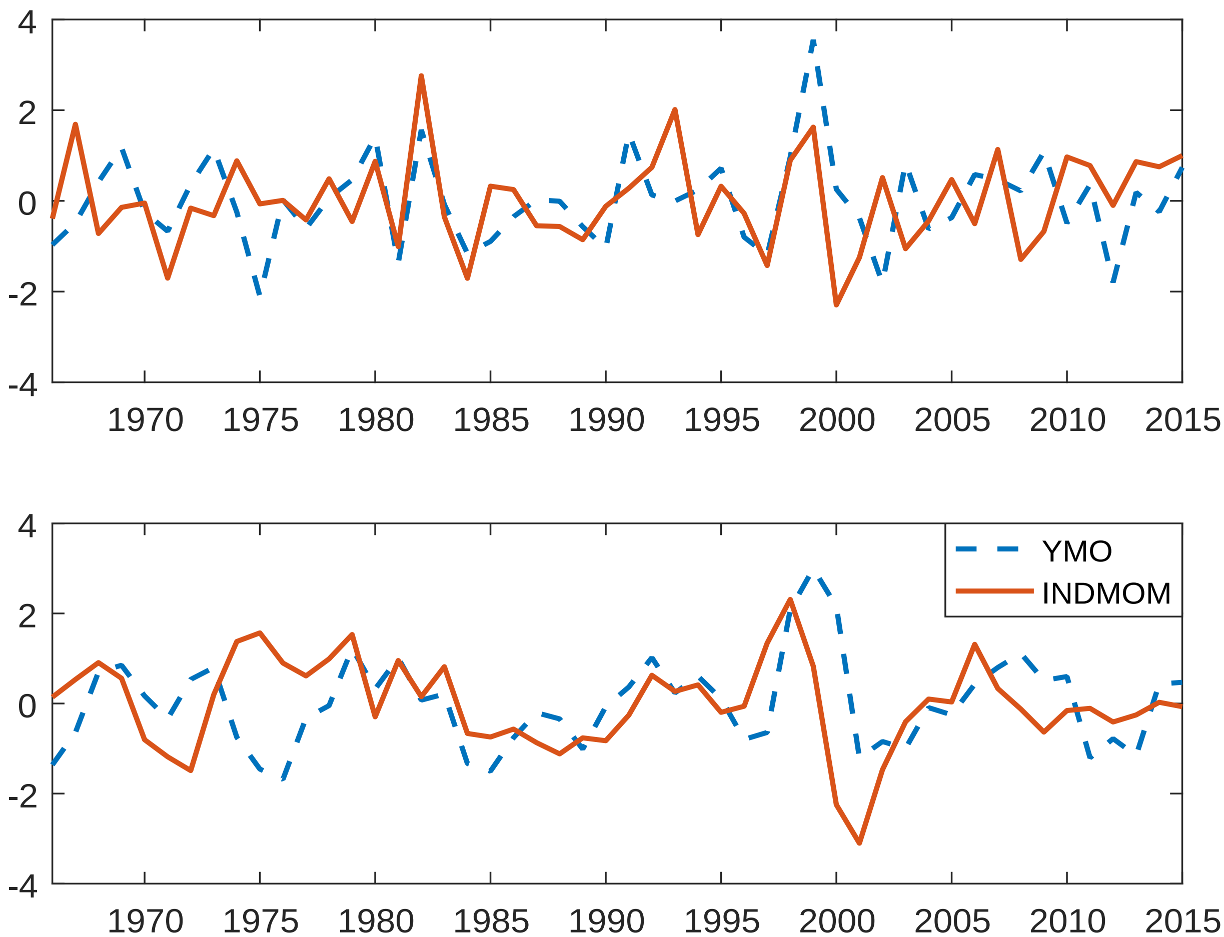
Notes: Table reports results from panel regressions using industry observations at the annual frequency from 1965 to 2014. Empirical regressions include industry and year fixed effects. t-statistics are based on standard errors clustered at the industry level. ω_t normalized to have unit standard deviation. ΔI is investment growth rate in equipment, software, and R&D. I/K is the quantity of investment divided by the quantity of fixed assets. $I_{t-3,t}$ is total investment from year $t-3$ to t. The left-hand variable is at the top of each column, the right-hand variable is in the first column. Regressions use 1,323 observations. Model-implied coefficients and t-statistics are averages across 500 simulations.

Figure 1: UMD and YMO



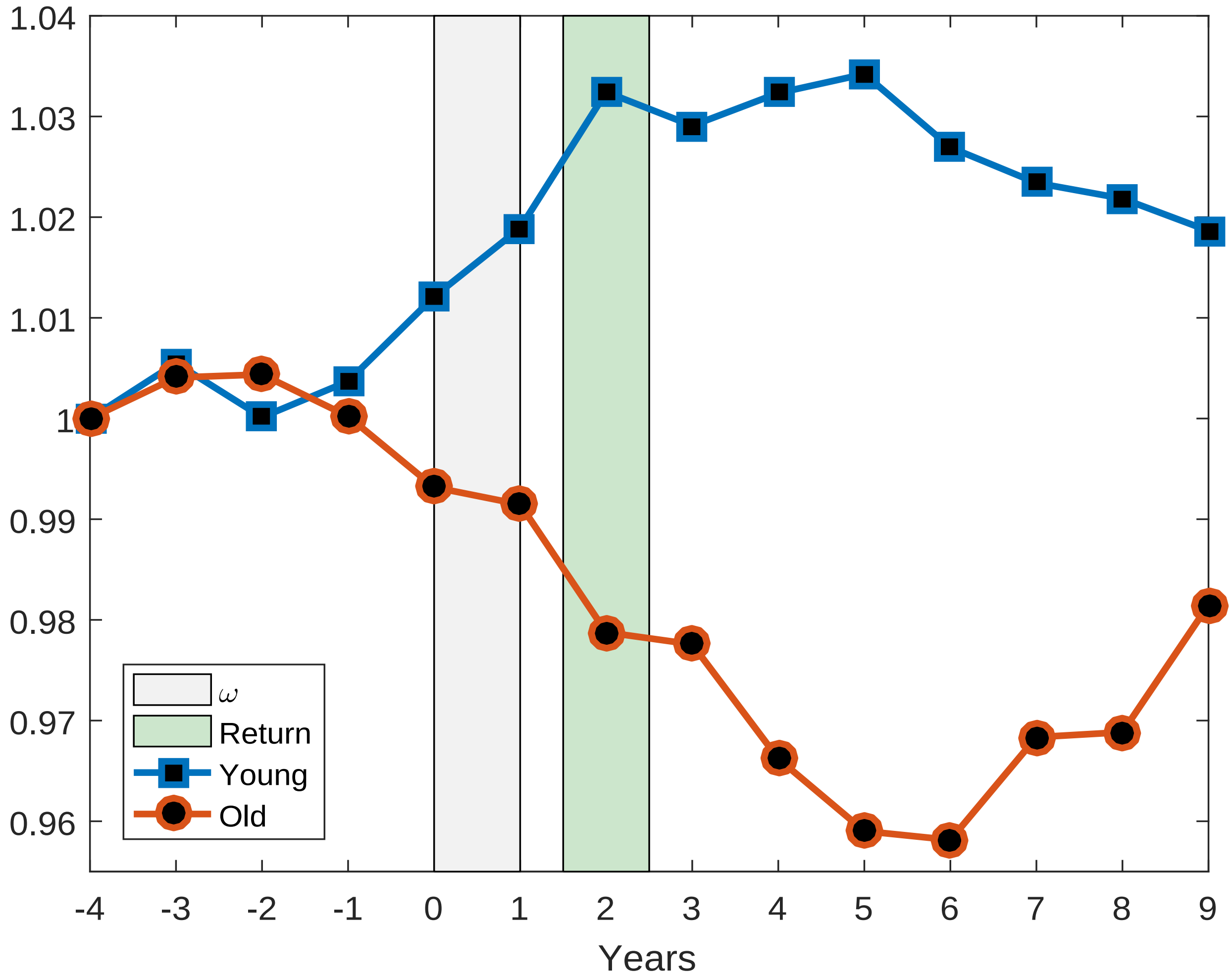
Notes: Figure plots the YMO spread and momentum factor (UMD) from Kenneth French's website. The top figure plots annual returns and the bottom figure plots three year average returns. All returns are normalized to have zero mean and unit standard deviation.

Figure 2: Industry Momentum



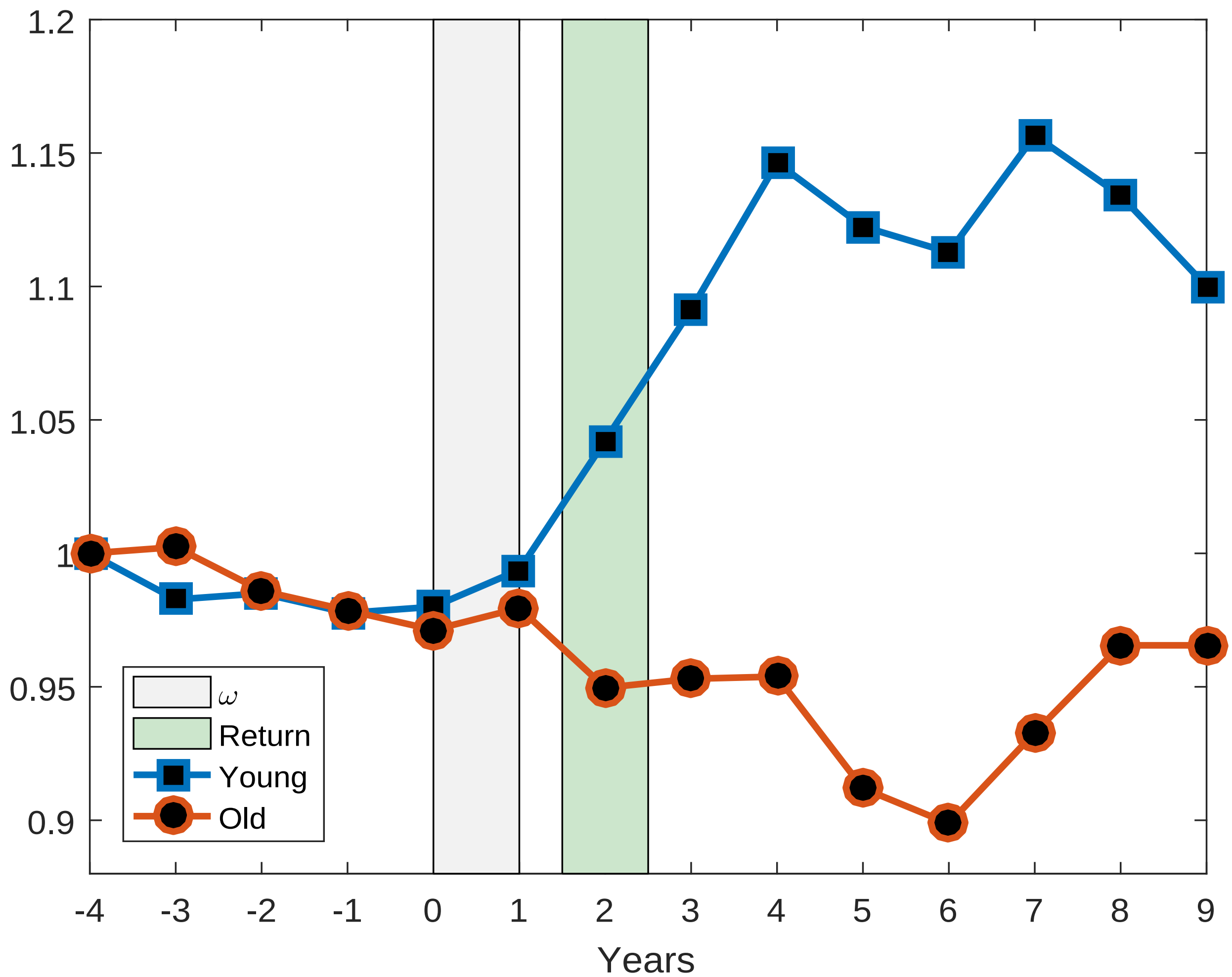
Notes: Figure plots the YMO spread and industry momentum returns (INDMOM) defined as the return differential between the six highest and lowest momentum industries among 30 industries from Kenneth French's website. The top figure plots annual returns and the bottom figure plots three year average returns. All returns are normalized to have zero mean and unit standard deviation.

Figure 3: Embodied Technology (IST Level)



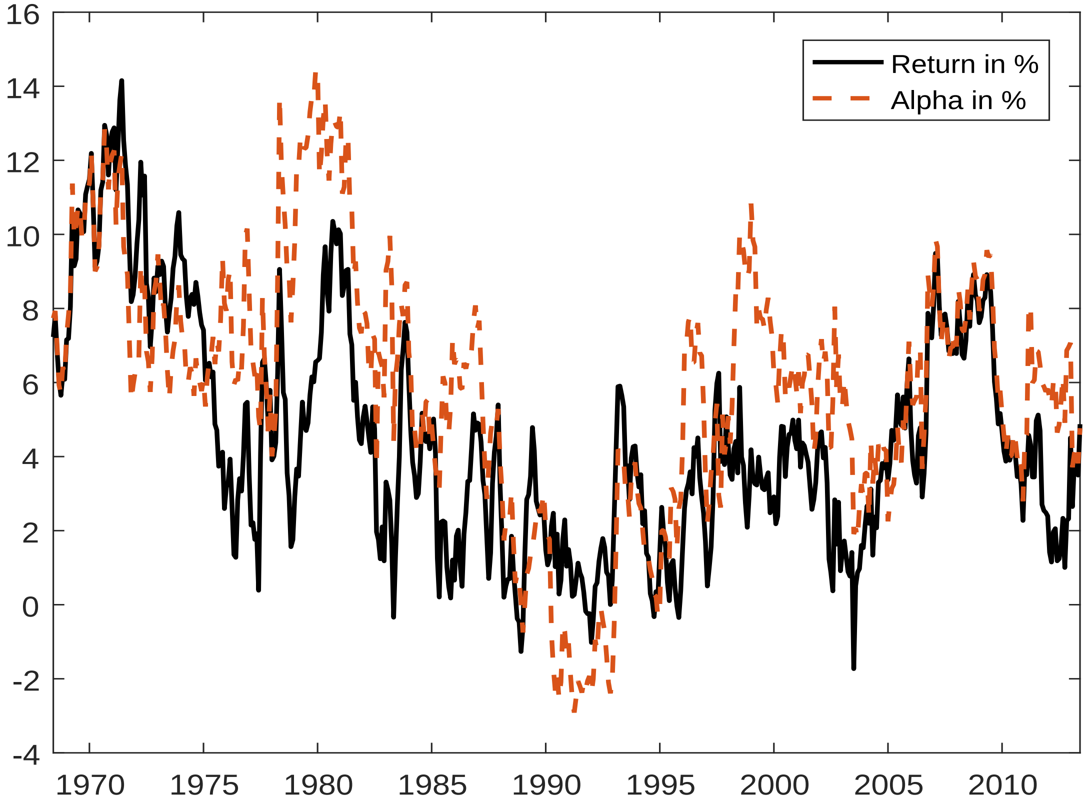
Notes: Figure plots the IST level for portfolio Y and O relative to the aggregate economy. The IST level is computed as the inverse of the relative price of investment at the industry level from KLEMS divided by the consumption deflator. Portfolio level quantities are computed using the average industry IST levels value-weighted by the quantity of investment. The IST level is normalized to one four years prior to portfolio formation. The gray area depicts the portfolio formation year, the green are depicts the year of return observation (YMO).

Figure 4: Investment



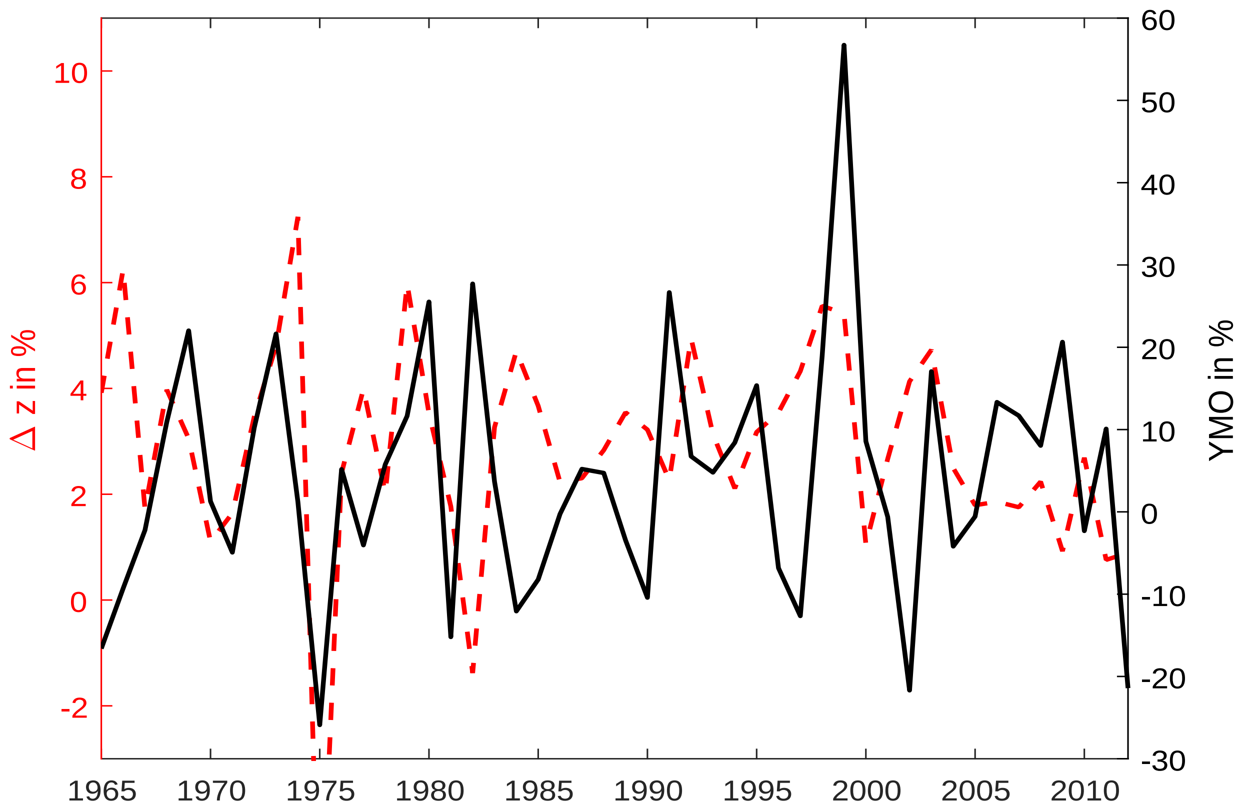
Notes: Investment for young and old hiring portfolios is constructed using quantity indices for equipment, software, and R&D from NIPA. Data are annual from 1965 to 2014. The gray area corresponds to the period where hiring measures are observed. The green area highlights the period expected returns are measured. Investment is normalized to one four years before portfolio formation, and the plotted series are computed using investment growth relative to the aggregate trend.

Figure 5: Five Year Average YMO Returns and Alphas



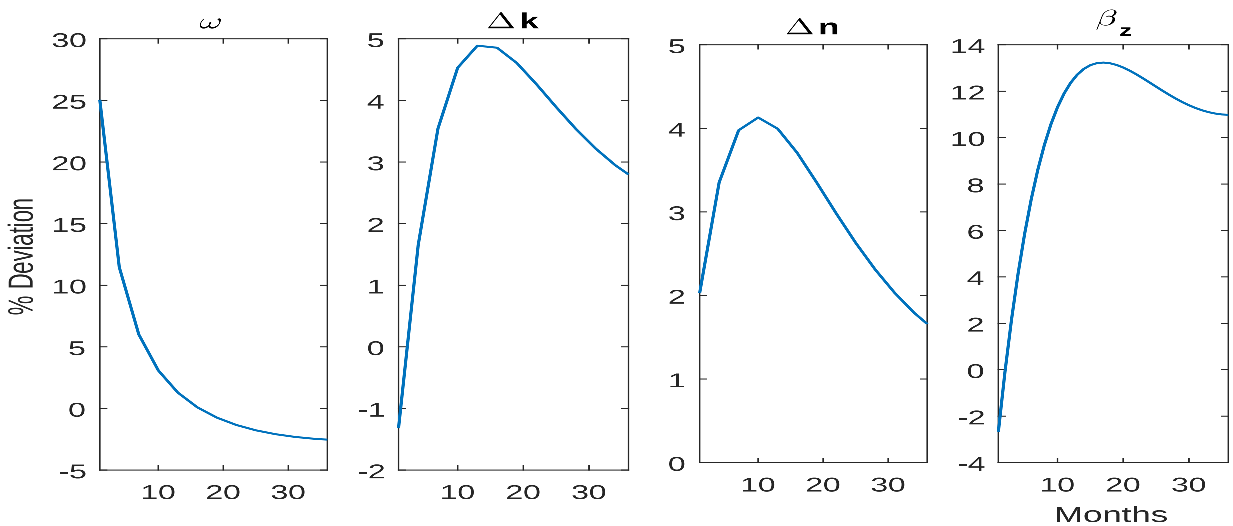
Notes: Figure plots 5-year average monthly YMO returns and rolling alphas from the Fama-French three-factor model.

Figure 6: Annual YMO Returns and IST shocks



Notes: Figure plots the annual return differential between portfolios Y and O (solid line) and annual log IST shocks (dashed line). IST shocks are measured as the growth in the inverse of the relative price of equipment and software. The average of IST shocks in the post-1982 period is equated to the pre-1982 average.

Figure 7: Model Impulse response to a shock to $\tilde{z}$



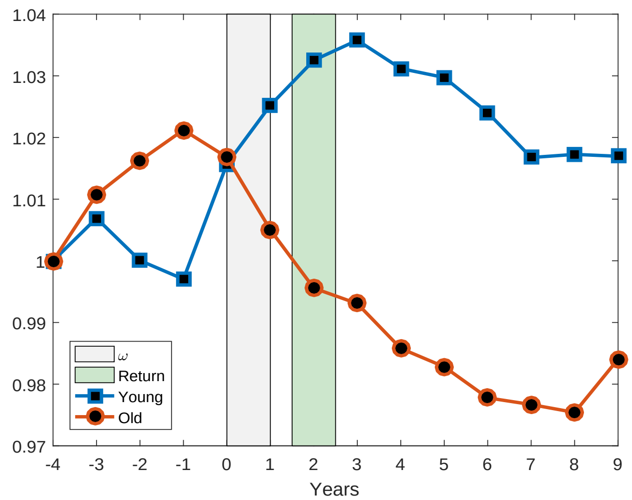
Notes: Figure plots the impulse response of Δk, Δn, ω to a one standard deviation shock to $\tilde{z}$. Δk is the growth of the capital stock, Δn is the growth of number of employees. ω is the hiring rate differential between young and old labor. β_z is the average 6-month loading of the stock return on the aggregate IST shock.

Table A.1: Wages and Aggregate Shocks

i	β_a	β_z	$\bar{R}^2$
	k = 1		
Y	0.37	0.28	0.34
	[3.53]	[2.60]	
O	0.68	-0.11	0.40
	[8.32]	[-0.83]	
Y - O	-0.72	0.61	0.24
	[-2.97]	[3.69]	
	k = 5		
Y	0.71	0.52	0.49
	[3.09]	[4.23]	
O	1.63	0.00	0.58
	[6.90]	[-0.01]	
Y - O	-0.91	0.52	0.32
	[-3.29]	[3.52]	
	k = 7		
Y	0.92	0.51	0.68
	[4.31]	[5.49]	
O	1.89	0.03	0.70
	[7.29]	[0.19]	
Y - O	-0.97	0.48	0.40
	[-3.85]	[3.26]	

Notes: Table reports results from regressions of the form $\Delta\log(w^i_{t\to t+k}) = \beta_0 + \beta_a\Delta\log(a_{t\to t+k}) + \beta_z\Delta\log(z_{t\to t+k})$. $\Delta\log(w_{t\to t+k})$ is the k-year average wage growth per employee in the aggregate economy. $\Delta\log(a_{t\to t+k})$ and $\Delta\log(z_{t\to t+k})$ are total factor productivity growth and investment-specific technology growth in the corresponding k years, respectively. Rows i =Y (i =O) include results for young (old) employees. Y - O uses $\log(w^Y_{t\to t+k}) - \log(w^O_{t\to t+k})$ as the independent variable. Data are annual and span the period from 1965 to 2015. See Appendix A for details of data sources and construction.

Figure A.1: Alternative Measure of Embodied Technology (IST Level)



Notes: This figure replicates Figure 3 using the industry-level price index for value added from KLEMS rather than the consumption deflator.

Table A.2: Model Moments with Unskilled Labor

	Data	Model		Data	Model
$\mathbb{E}[r_m - r_f]$	6.29	4.88	$\sigma(h/n)$ XS	0.26	0.11
$\sigma(r_m)$	18.10	14.01	$\sigma(h/n)$ TS	0.23	0.09
$\mathbb{E}[r_y - r_o]$	4.64	5.75	$\sigma(i/k)$ XS	0.21	0.16
$\mathbb{E}[r_v - r_g]$	6.04	3.49	$\sigma(i/k)$ TS	0.23	0.18
$\mathbb{E}[r_l - r_h]$	5.61	3.07	Wages/Sales (value)	0.68	0.65
$corr(r_v - r_g, r_y - r_o)$	-0.28	-0.16	Wages/Sales (growth)	0.53	0.54

Notes: See Table 17 for variable definitions.

Table A.3: Model Moments with Transition From Young to Old

	Data	Model		Data	Model
$\mathbb{E}[r_m - r_f]$	6.29	5.17	$\sigma(h/n)$ XS	0.26	0.14
$\sigma(r_m)$	18.10	14.82	$\sigma(h/n)$ TS	0.23	0.15
$\mathbb{E}[r_y - r_o]$	4.64	6.75	$\sigma(i/k)$ XS	0.21	0.15
$\mathbb{E}[r_v - r_g]$	6.04	3.78	$\sigma(i/k)$ TS	0.23	0.16
$\mathbb{E}[r_l - r_h]$	5.61	3.32	Wages/Sales (value)	0.68	0.70
$corr(r_v - r_g, r_y - r_o)$	-0.28	-0.16	Wages/Sales (growth)	0.53	0.48

Notes: See Table 17 for variable definitions.

Table A.4: Demographic Shifts and Investment Controlling for Past Investment Rate

Panel A: Relation to future investment growth				
	$\Delta I_{t,t+1}$	$\Delta I_{t,t+1}$	$\Delta I_{t,t+3}$	$\Delta I_{t,t+3}$
ω_t	7.73	8.37	23.71	18.46
	[4.45]	[3.05]	[6.51]	[3.48]
$I_{t-1,t}/K_{t-1}$	-0.18	-0.74	-0.28	-1.51
	[-2.23]	[2.51]	[-1.18]	[-3.23]
R^2 in %	3.97	60.98	8.84	66.20
FE	N	Y	N	Y

Panel B: Relation to future investment rate				
	I_{t+1}/K_t	I_{t+1}/K_t	$I_{t+1,t+3}/K_t$	$I_{t+1,t+3}/K_t$
ω_t	1.59	1.69	9.94	5.72
	[6.09]	[3.08]	[7.92]	[3.24]
$I_{t-1,t}/K_{t-1}$	0.83	0.73	2.65	2.14
	[8.58]	[2.51]	[8.18]	[7.14]
R^2 in %	64.28	87.41	57.08	85.25
FE	N	Y	N	Y

Notes: Table reports results from panel regressions using industry observations at the annual frequency from 1965 to 2014. FE is fixed effects. Columns with N are without, Y with industry and year fixed effects. t-statistics are based on standard errors clustered at the industry level. Coefficients on ω_t are multiplied by 100. ω_t normalized to have unit standard deviation. ΔI is investment growth rate in equipment, software, and R& D. I/K is the quantity of investment divided by the quantity of fixed assets. $I_{t+1,t+3}$ is total investment from year $t+1$ to $t+3$. The left-hand variable is at the top of each column, the right-hand variables are ω_t and $I_{t-1,t}/K_{t-1}$ where $\omega_t = \log(l_t^y/l_{t-1}^y) - \log(l_t^o/l_{t-1}^o)$. Regressions use 1,323 observations.

Table A.5: Demographic Composition in Levels and Investment

Panel A: Relation to future investment growth						
	$\Delta I_{t,t+1}$	$\Delta I_{t,t+1}$	$\Delta I_{t,t+3}$	$\Delta I_{t,t+3}$	$\Delta I_{t-1,t}$	$\Delta I_{t-1,t}$
$\log(l_t^y/l_t^o)$	2.31	-1.66	5.99	-6.46	2.72	-1.09
	[2.66]	[-1.03]	[2.52]	[-2.06]	[1.68]	[-1.05]
R^2 in %	2.18	59.79	5.06	63.69	2.93	58.63
FE	N	Y	N	Y	N	Y

Panel B: Relation to future investment rate						
	I_{t+1}/K_t	I_{t+1}/K_t	$I_{t+1,t+3}/K_t$	$I_{t+1,t+3}/K_t$	I_t/K_{t-1}	I_t/K_{t-1}
$\log(l_t^y/l_t^o)$	5.10	0.38	18.71	0.97	5.13	0.71
	[5.30]	[0.45]	[6.65]	[0.31]	[6.64]	[0.72]
R^2 in %	32.18	71.37	37.25	72.98	32.60	71.02
FE	N	Y	N	Y	N	Y

Notes: Table reports results from panel regressions using industry observations at the annual frequency from 1965 to 2014. FE is fixed effects. Columns with N are without, Y with industry and year fixed effects. t-statistics are based on standard errors clustered at the industry level. All coefficients are multiplied by 100. ω_t normalized to have unit standard deviation. ΔI is investment growth rate in equipment, software, and R& D. I/K is the quantity of investment divided by the quantity of fixed assets. $I_{t+1,t+3}$ is total investment from year $t+1$ to $t+3$. The left-hand variable is at the top of each column, the right-hand variable is $\log(l_t^y/l_t^o)$. Regressions use 1,323 observations.

Table A.6: Predicting Demographic Composition with Investment

Panel A: Predicting with investment growth				
	ω_{t+1}	ω_{t+1}	$\log(l_t^y/l_t^o)$	$\log(l_t^y/l_t^o)$
$\Delta I_{t-1,t}$	0.08		0.72	
	[1.65]		[7.10]	
$\Delta I_{t-3,t}$		0.03		0.66
		[0.60]		[8.40]
R^2 in %	60.16	60.01	72.47	79.85
Panel B: Predicting with investment rate				
I_t/K_{t-1}	0.15		6.64	
	[0.85]		[4.85]	
$I_{t-3,t}/K_{t-4}$		-0.02		2.19
		[-0.37]		[5.40]
R^2 in %	60.16	60.01	82.47	84.85

Notes: Table reports results from panel regressions using industry observations at the annual frequency from 1965 to 2014. Regressions include industry and year fixed effects. t-statistics are based on standard errors clustered at the industry level. ω_t normalized to have unit standard deviation. ΔI is investment growth rate in equipment, software, and R& D. I/K is the quantity of investment divided by the quantity of fixed assets. $I_{t-3,t}$ is total investment from year $t-3$ to t. The left-hand variable is at the top of each column, the right-hand variable is in the first column. Regressions use 1,323 observations.

Table A.7: Future Investment, TFP, and Demographic Shifts

	ω_t			
$\Delta I_{t,t+3}$	0.21	0.23	0.22	0.23
	[3.50]	[1.84]	[3.19]	[1.62]
$a_{t,t+3}$			-0.03	-0.02
			[-0.74]	[-0.60]
$a_{t,t+3} \cdot \Delta I_{t,t+3}$		-0.09		-0.09
		[-3.07]		[2.61]
R^2	0.64	0.65	0.64	0.66
FE	Y	Y	Y	Y

Notes: Table reports results from four regressions of ω_t on investment growth over the next three years ($\Delta I_{t,t+3}$), industry level TFP over the three years ($a_{t,t+3}$), and an interaction term. Industry-level TFP data are from KLEMS. Regressions include year and industry fixed effects. t-statistics are based on standard errors clustered at the industry level. ω_t, $z_{t,t+3}$, and $\Delta I_{t,t+3}$ are normalized to have unit standard deviation across all industry-year observations. ΔI is investment growth rate in equipment, software, and R& D. All regressions use 1,323 industry-year observations from 1966 to 2014.

Table A.8: Wage Dynamics

Panel A: Wage growth per employee						
	Young			Old		
	Y	M	O	Y	M	O
$t-2$	0.21	0.91	1.69	0.53	0.89	1.29
$t-1$	0.65	0.97	0.32	0.29	1.18	0.53
t	1.92	1.55	0.33	1.28	1.25	0.29
$t+1$	0.43	1.21	0.99	0.81	1.14	0.45
$t+2$	0.98	0.99	1.03	0.61	0.85	1.05
$t+3$	0.92	1.07	0.03	0.93	0.98	0.14
Panel B: Wage bill growth						
	Young			Old		
$t-2$	7.01	5.72	7.39	6.24	5.55	10.07
$t-1$	8.51	5.94	4.06	8.25	6.29	5.55
t	11.32	6.02	2.72	5.12	5.93	7.94
$t+1$	5.75	5.46	3.55	5.23	5.74	3.54
$t+2$	5.61	4.61	3.43	5.29	5.12	5.26
$t+3$	4.73	4.75	1.52	5.11	5.26	4.13

Notes: Panel A reports average wage growth per young and old skilled employee in industries in portfolio Y, M, O in year t. Panel B reports the same statistic for total wages of young and old skilled employees. The period covers from 1965 to 2015.

Table A.9: Wage Costs

	Y	M	O
Panel A: Wage costs			
$t-2$	0.83	0.86	0.85
$t-1$	0.85	0.86	0.85
t	0.83	0.85	0.84
$t+1$	0.85	0.85	0.84
$t+2$	0.85	0.86	0.84
$t+3$	0.84	0.85	0.83
Panel B: Labor share			
$t-2$	0.50	0.52	0.50
$t-1$	0.48	0.53	0.48
t	0.47	0.52	0.48
$t+1$	0.48	0.51	0.48
$t+2$	0.47	0.52	0.47
$t+3$	0.48	0.51	0.47
Panel C: Operating leverage			
$t-2$	0.61	0.58	0.69
$t-1$	0.66	0.61	0.71
t	0.68	0.59	0.72
$t+1$	0.67	0.56	0.67
$t+2$	0.65	0.58	0.64
$t+3$	0.62	0.59	0.65

Notes: Panel A reports average ratio of total wages to total costs in industries in the time-t portfolio Y, M, O. Total costs are the sum of costs of goods sold, sales, general, and administrative expense, and wages. Panel B reports average labor shares computed as the ratio of wages to revenues in an industry. Panel C reports operating leverage computed as in Novy-Marx (2011). The period covers from 1965 to 2015.

Table A.10: Workforce Composition Dynamics

	Y	M	O
ω_t	0.05	0.00	-0.06
ω_{t+1}	0.03	-0.01	-0.02
ω_{t+2}	0.02	0.00	-0.01
ω_t^s	0.03	0.03	0.03
$age_{ceo,t}$	61.43	62.33	62.56
$\Delta age_{ceo,t}$ in %	-0.69	-0.61	-0.66
Quit rate at t in%	2.28	2.16	2.38
Quit rate at $t+1$ in%	2.23	2.19	2.41
Quit rate at $t+2$ in%	2.32	2.21	2.30
Quit rate at $t+3$ in%	2.26	2.26	2.35

Notes: Table reports averages of variables related to workforce dynamics or portfolios Y, M, and O that are formed in year t based on ω_t. $\omega_t = \log(l_t^y/l_{t-1}^y) - \log(l_t^o/l_{t-1}^o)$ where l^y and l^o is the number of young and old skilled employees, respectively. $w_t^s = \log(l_t^s/l_{t-1}^s) - \log(l_t^u/l_{t-1}^u)$ where l_s and l_o is the number of skilled and unskilled employees, respectively. These data are in annual frequency from 1965 to 2015. age_{ceo} is the average age of CEOs from Execucomp for firms in the corresponding portfolios from 1990 to 2014. $\Delta age_{ceo,t}$ is the change in average CEO age from year $t-1$ to t. Quit rate is the ratio of monthly total quits to total number of employees in in industries computed using data from 2000 to 2015 from JOLTS.

Table A.11: Portfolio Transitions

	Y	M	O
		1 year	
Y	0.42	0.44	0.13
M	0.14	0.73	0.13
O	0.12	0.51	0.37
		3 years	
Y	0.52	0.85	0.36
M	0.39	0.91	0.34
O	0.35	0.83	0.58
		5 years	
Y	0.67	0.93	0.37
M	0.53	0.95	0.48
O	0.38	0.92	0.68

Notes: Table reports portfolio transition rates. Rows correspond to portfolio in year t, column to the future portfolio. 3 years and 5 years report the probability of spending at least one year in the corresponding portfolio from $t+1$ to $t+3$ or $t+5$, respectively.

Table A.12: Firm Expansions and Entry

	Y	M	O	Y - O
Year $t-1$ to t				
Gains	2.12	1.43	1.87	0.25
Expansions	1.76	2.13	1.92	-0.16
Openings	2.45	1.17	1.32	1.13
Losses	1.32	0.76	0.96	0.87
Contractions	1.12	0.45	0.24	-1.12
Closings	2.76	3.31	1.34	1.42
Year t to $t+1$				
Gains	2.48	1.14	1.92	0.56
Expansions	1.13	2.21	2.15	-1.02
Openings	6.42	-0.89	-2.34	8.76
Losses	1.32	0.38	2.13	-0.81
Contractions	0.34	0.27	1.97	-1.63
Closings	4.12	3.24	2.68	1.44

Notes: Table reports the annual growth rates of job gains and losses for the portfolio formation year and the subsequent year as reported in Business Employment Dynamics by BLS. Gains are reported for both expansions and openings. Losses are reported for both contractions and closings. Data are annual from 1990 to 2014. t-statistics are not reported for brevity. The only significant difference in the Y - O column with a t-statistic of 2.14 is openings from t to $t+1$.

Table A.13: Cash-Flow Predictability (1-year)

Young-Old hiring spread				
	Y	M	O	Y - O
Δa	3.41	0.02	2.58	0.82
				[0.25]
Δz	2.12	0.96	-2.64	4.76
				[2.49]
R^2	0.01	-0.02	-0.01	0.05
Value versus growth				
	V	M	G	V - G
Δa	14.12	1.51	-2.66	16.78
				[2.99]
Δz	0.05	-0.09	-1.05	1.11
				[0.51]
R^2	0.13	-0.02	-0.02	0.17
Industry momentum				
	W	M	L	W - L
Δa	-8.62	2.74	5.14	-13.80
				[-2.17]
Δz	7.81	0.29	-2.02	9.82
				[2.61]
R^2	0.05	-0.01	0.01	0.15

Notes: Table reports results from predictive regressions of the form $\Delta d_{t+1} = \beta_0 + \beta_a \Delta a_{t-3,t} + \beta_z \Delta z_{t-3,t}$ where Δd_{t+1} is the annual log dividend growth, $\Delta a_{t-3,t}$ is the sum of annual log TFP shock from last three years, $\Delta z_{t-3,t}$ is the sum of annual log IST shock from last three years, $t-2$ is the portfolio formation year. Both of these aggregate shocks are normalized to have unit standard deviation. Coefficients are multiplied by 100. Portfolio dividends are computed following Bansal, Dittmar, Lundblad (2005). V, M, and G are high, medium, and low B/M portfolios where the cutoff values are 30% and 70% of a year's B/M distribution among NYSE stocks. W, M, and L are winner, medium, and loser industries based on last year's returns. t-statistics are based on Newey-West standard errors. The data period is from 1965 to 2015.

Table A.14: Cash-Flow Predictability (3-year)

Young-Old hiring spread				
	Y	M	O	Y - O
β_a	-7.82	-6.92	-2.61	-5.21
				[-0.90]
β_z	25.15	7.15	3.83	21.31
				[3.97]
R^2	0.27	0.02	-0.01	0.25
Value versus growth				
	V	M	G	V - G
β_a	7.33	-6.83	-23.40	30.74
				[2.87]
β_z	11.84	9.64	2.59	9.25
				[0.94]
R^2	0.01	0.05	0.24	0.18
Industry momentum				
	W	M	L	W - L
β_a	-7.66	-7.18	-5.49	-2.17
				[-0.31]
β_z	31.13	13.37	-0.81	31.94
				[4.86]
R^2	0.30	0.14	-0.01	0.35

Notes: Table reports results from predictive regressions of the form $\Delta d_{t+1,t+3} = \beta_0 + \beta_a \Delta a_{t-3,t} + \beta_z \Delta z_{t-3,t}$ where $\Delta d_{t+1,t+3}$ is the annual log dividend growth over the next three years, $\Delta a_{t-3,t}$ is the sum of annual log TFP shock from last three years, $\Delta z_{t-3,t}$ is the sum of annual log IST shock from last three years. Both of these aggregate shocks are normalized to have unit standard deviation. Coefficients are multiplied by 100. Portfolio dividends are computed following Bansal, Dittmar, Lundblad (2005). V, M, and G are high, medium, and low B/M portfolios where the cutoff values are 30% and 70% of a year's B/M distribution among NYSE stocks. W, M, and L are winner, medium, and loser industries based on last year's returns. t-statistics are based on Newey-West standard errors. The data period is from 1965 to 2015.

Table A.15: Cash-Flow Predictability (1-year) in subsamples

1990 - 2015				
	Y	M	O	Y - O
β_a	8.15	4.92	13.75	-2.59
				[-0.42]
β_z	2.51	-1.53	-9.29	11.80
				[2.31]
R^2	0.09	-0.02	0.15	0.05
1965 - 1990				
	Y	M	O	Y - O
β_a	-1.23	-2.92	-1.22	-0.00
				[-0.01]
β_z	1.07	2.34	-7.39	8.46
				[2.95]
R^2	-0.01	-0.01	0.04	0.04

Notes: Table reports results from predictive regressions of the form $\Delta d_{t+1,t+3} = \beta_0 + \beta_a \Delta a_{t-3,t} + \beta_z \Delta z_{t-3,t}$ where $\Delta d_{t+1,t+3}$ is the annual log dividend growth over the next three years, $\Delta a_{t-3,t}$ is the sum of annual log TFP shock from last three years, $\Delta z_{t-3,t}$ is the sum of annual log IST shock from last three years. Both of these aggregate shocks are normalized to have unit standard deviation. Coefficients are multiplied by 100. Portfolio dividends are computed following Bansal, Dittmar, Lundblad (2005). t-statistics are based on Newey-West standard errors. The data periods are from 1965 to 1990 and 1990 to 2015.

Table A.16: Cash-Flow Predictability (3-year) in subsamples

	Y	M	O	Y - O
1990 - 2015				
β_a	-2.20	-12.75	7.42	-9.63
				[-0.94]
β_z	19.17	11.34	-0.35	19.52
				[3.97]
R^2	0.07	-0.02	-0.02	0.10
1965 - 1990				
	Y	M	O	Y - O
β_a	-1.05	-3.20	8.26	-9.31
				[-0.39]
β_z	12.61	2.80	-1.24	13.85
				[2.95]
R^2	0.14	-0.01	0.04	0.23

Notes: Table reports results from predictive regressions of the form $\Delta d_{t+1,t+3} = \beta_0 + \beta_a \Delta a_{t-3,t} + \beta_z \Delta z_{t-3,t}$ where $\Delta d_{t+1,t+3}$ is the annual log dividend growth over the next three years, $\Delta a_{t-3,t}$ is the sum of annual log TFP shock from last three years, $\Delta z_{t-3,t}$ is the sum of annual log IST shock from last three years. Both of these aggregate shocks are normalized to have unit standard deviation. Coefficients are multiplied by 100. Portfolio dividends are computed following Bansal, Dittmar, Lundblad (2005). t-statistics are based on Newey-West standard errors. The data periods are from 1965 to 1990 and 1990 to 2015.

Table A.17: Rolling Factor Regressions with YMO

1-year			
α	3.39	4.77	4.18
	[3.10]	[3.25]	[2.68]
MKT	0.10	-0.01	-0.03
	[2.47]	[-0.26]	[-0.87]
SMB		0.05	0.07
		[0.90]	[1.28]
HML		-0.29	-0.25
		[-3.28]	[-2.26]
INV			0.12
			[0.99]
PROF			0.05
			[0.35]
3-year			
α	3.72	4.85	6.13
	[3.17]	[3.37]	[3.82]
MKT	0.11	0.03	0.01
	[2.78]	[1.08]	[0.08]
SMB		-0.03	-0.04
		[-0.70]	[-0.85]
HML		-0.21	-0.18
		[-3.42]	[-2.20]
INV			0.06
			[0.83]
PROF			-0.01
			[-0.12]

Notes: Table reports average coefficient estimates from rolling CAPM, Fama-French three-factor and five-factor models. Data are monthly from 1966 to 2015. t-statistics are based on GMM standard errors used to compute averages and rolling time series of factor loadings.

Table A.18: Properties of ω

	Y	M	O	All
Mean	0.05	0.00	-0.06	-0.00
Median	0.04	-0.01	-0.07	-0.01
5%	-0.06	-0.12	-0.16	-0.12
95%	0.24	0.13	0.06	0.15
SD	0.11	0.09	0.09	0.10
Skewness	1.27	0.67	0.19	0.81

Notes: Table reports summary statistics for industry-year observations of $\omega_t = \log(l_t^y/l_{t-1}^y) - \log(l_t^o/l_{t-1}^o)$. Columns Y, M, and O include industries in the corresponding portfolios. The last column includes all industry-year observations. The data period is from 1966 to 2015.

Table A.19: Alternative Measures of Demographic Shifts

	(1)	(2)
Panel A: YMO		
	4.41	3.96
	[2.78]	[2.38]
Panel B: Fama-French 5 factor		
α	6.01	4.85
	[3.01]	[2.98]
MKT	0.04	0.02
	[0.72]	[0.29]
SMB	-0.14	0.03
	[-1.07]	[0.46]
HML	-0.18	-0.26
	[-2.12]	[-2.41]
INV	0.05	-0.12
	[0.22]	[-0.94]
PROF	-0.03	0.02
	[-0.09]	[0.08]

Notes: Panel A reports YMO, the difference between the returns of young and old hiring portfolios, for alternative measures of ω_t:

(1) $\omega_t = l_t^y / l_{t-1}^y - l_t^o / l_{t-1}^o$,
(2) $\omega_t = (\Delta l_t^y - \Delta l_t^o)/(l_t^y + l_t^o)$.

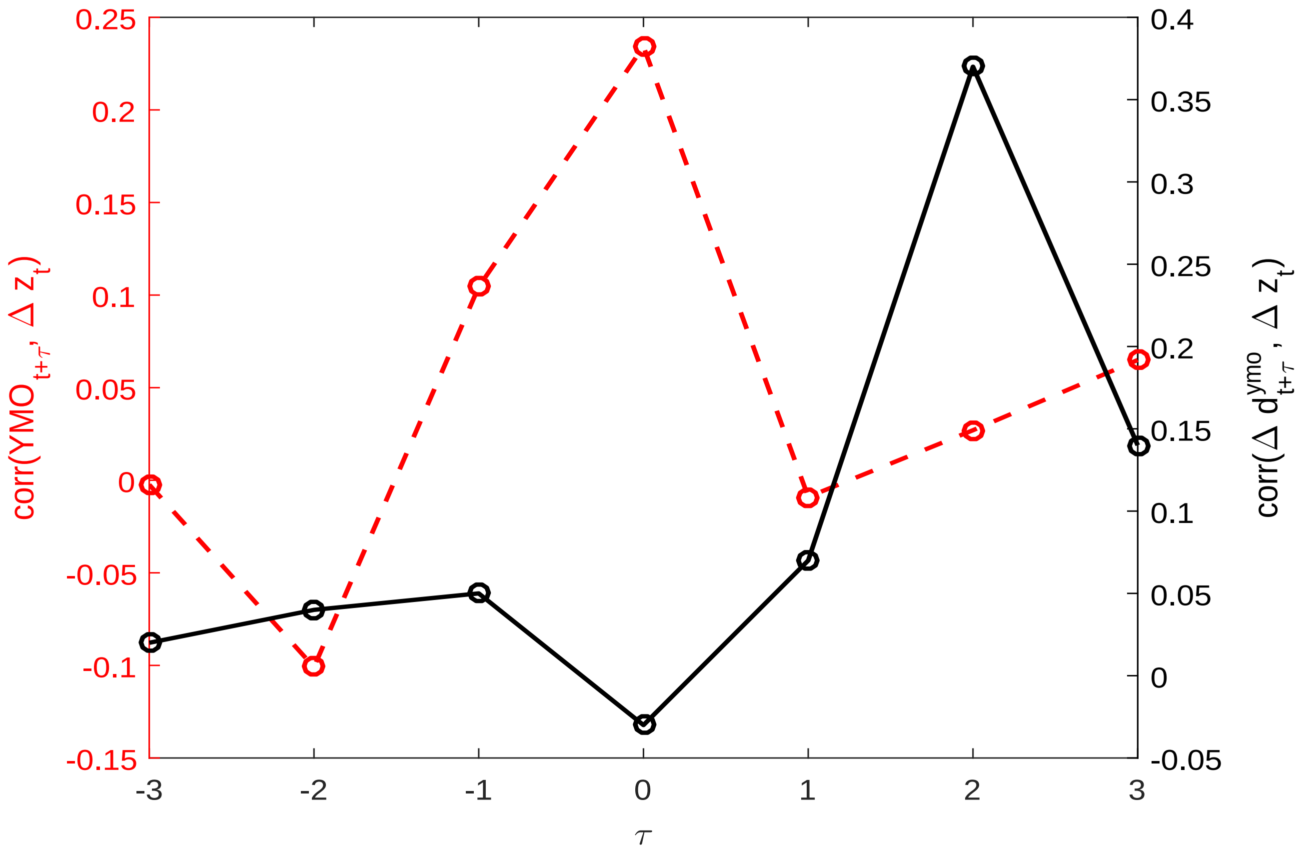
Panel B reports results from time-series regressions of YMO using the Fama and French (2015) 5-factor model. t-statistics in brackets are based on Newey-West standard errors.

Table A.20: Sample of Industries in the Young Hiring Portfolio

1966 - 1975	1976 - 1980	1981 - 1990
Print & Publish	Measuring & control eq.	Chemicals
Telecom	Machinery	Transport eq.
Oil & mining	Print & publish	Construction
1996 - 2000	**2001 - 2010**	**2011 - 2015**
Telecom	Business services	Manufacturing & recycling
Electrical & optical eq.	Electrical & optical eq.	Transport eq.
Chemicals	Finance	Business services

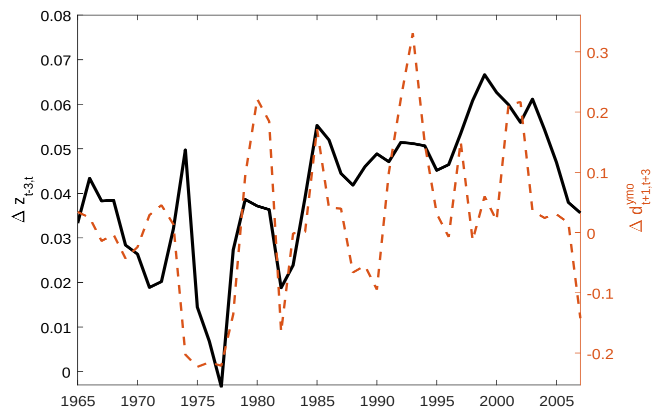
Notes: Table lists a sample of ISIC industries that spend the most time in the young portfolio in the corresponding periods.

Figure A.2: Correlations between Annual YMO Returns and IST shocks



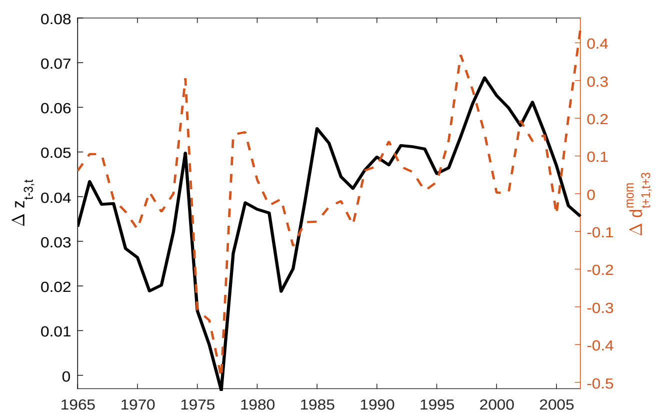
Notes: Figure plots the correlations of annual IST shocks with leads and lags of the the annual return differential between portfolios Y and O (dashed line line) and with the annual dividend growth differential between portfolios Y and O (solid line).

Figure A.3: YMO cash-flows and IST shocks



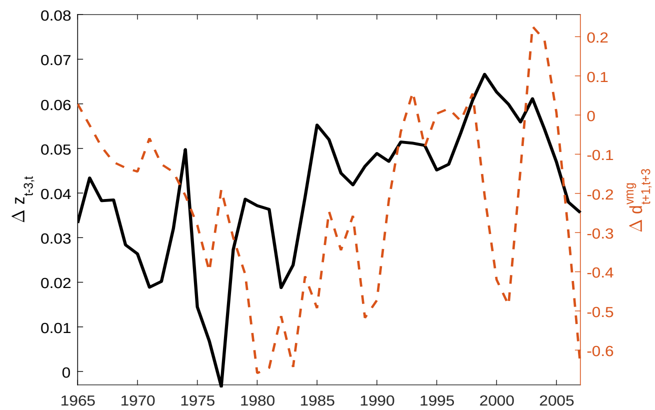
Notes: Figure plots the average of log IST shocks over the last three years (black line) and the log dividend growth differential between industries in portfolio Y and O (dashed line). IST shocks are measured as the growth in the inverse of the relative price of equipment and software.

Figure A.4: INDMOM cash-flows and IST shocks



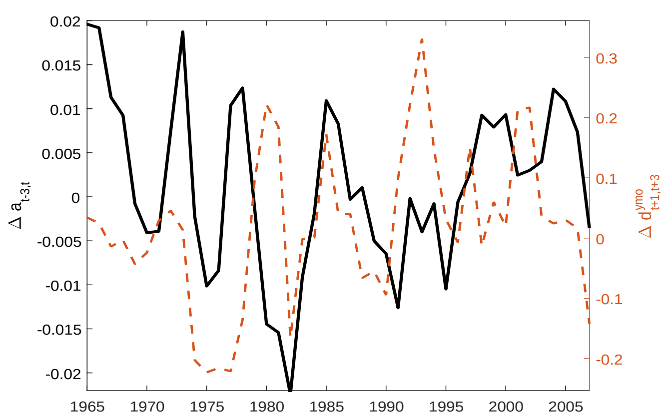
Notes: Figure plots the average of log IST shocks over the last three years (black line) and the log dividend growth differential between winner and loser industries used to compute industry momentum (dashed line). IST shocks are measured as the growth in the inverse of the relative price of equipment and software.

Figure A.5: Value-growth cash-flows and IST shocks



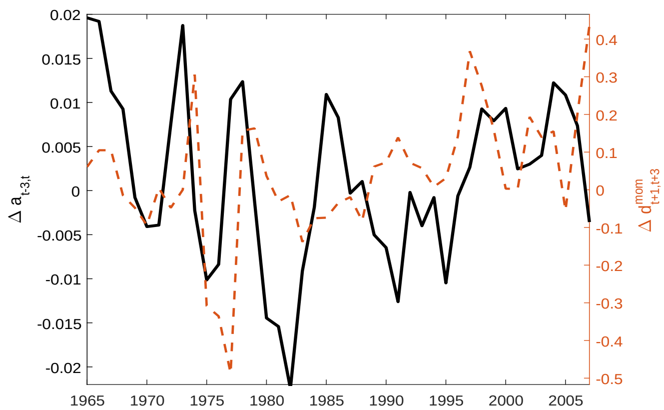
Notes: Figure plots the average of log IST shocks over the last three years (black line) and the log dividend growth differential between value and growth stocks based on the book-to-market ratio (dashed line). IST shocks are measured as the growth in the inverse of the relative price of equipment and software.

Figure A.6: YMO cash-flows and TFP shocks



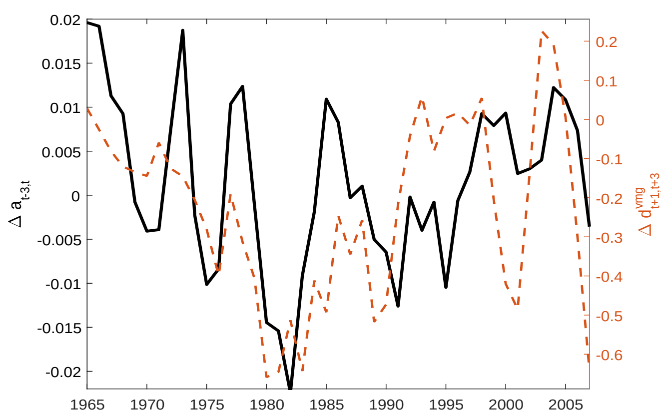
Notes: Figure plots the average of log TFP shocks over the last three years (black line) and the log dividend growth differential between industries in portfolio Y and O (dashed line).

Figure A.7: INDMOM cash-flows and TFP shocks



Notes: Figure plots the average of log TFP shocks over the last three years (black line) and the log dividend growth differential between winner and loser industries used to compute industry momentum (dashed line).

Figure A.8: Value-growth cash-flows and TFP shocks



Notes: Figure plots the average of log TFP shocks over the last three years (black line) and the log dividend growth differential between value and growth stocks based on the book-to-market ratio (dashed line).