Aggregate Corporate Savings, Economic Uncertainty and Future Stock Returns *

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Abstract

I find both U.S. and international evidence that aggregate corporate cash savings strongly negatively predict future excess market returns, and demonstrate economic uncertainty as an important driver of this relationship. In a calibrated neoclassical dynamic model highlighting firms' precautionary saving motives, I show that fixed financing costs, firm exit, and a time-varying price of risk induced by uncertainty are essential for the model to replicate the observed return predictability. These findings shed light on the puzzling positive correlation between aggregate accruals and future returns: after controlling for aggregate cash savings and capital investment, aggregate accruals have a near-zero relation with future market returns.

Keywords: Aggregate corporate savings, economic uncertainty, future stock market returns, aggregate accruals

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1 Introduction

A 2021 article from *The Wall Street Journal* highlighted the record amount of cash held by companies amid ongoing uncertainty related to the Covid-19 pandemic. Interestingly, the subsequent year, 2022, witnessed a prolonged downturn in the U.S. stock market. This correlation might not be simply coincidental. Prior research shows that firms tend to accumulate cash as a precaution during uncertain times (e.g., Bates et al., 2009; Riddick and Whited, 2009; Begenau and Palazzo, 2021), and that elevated uncertainty is empirically associated with lower future output and equity returns (e.g., Maio, 2016; Bloom et al., 2018). Motivated by these observations, I examine the time-series correlation between aggregate corporate cash savings and future market returns, and further investigate the role of economic uncertainty in driving this correlation.

This paper presents four main empirical findings and develops a neoclassical dynamic model that offers an economic rationale and quantitatively accounts for these results. First, aggregate corporate savings exhibit a robust negative correlation with future excess market returns across both U.S. and international markets. Second, this relationship is largely attributable to firms' risk-free financial asset investment behavior, as evidenced by the significant contributions of cash flows from financing and operating asset investing activities. Third, economic uncertainty accounts for a substantial portion of the observed correlation and is associated in similar patterns with firm cash flows. Fourth, the return predictive power of cash savings is concentrated among firms more sensitive to uncertainty, such as firms in R&D-intensive industries and those with low book-to-market (BM) ratios. The model features fluctuating productivity variance (i.e., economic uncertainty) and a time-varying price of risk that decreases with uncertainty. Elevated uncertainty increases firm productivity variance, raising the option value of cash holdings, while lowering the price of risk and expected equity premia. Together, these effects generate a negative association between changes in cash holdings and subsequent excess market returns.

Turning to empirical details, aggregate corporate savings exhibit strong in-sample return predictive power, with an annual adjusted R^2 of 13.9%.[1] This predictive ability also holds out-of-sample. Using the methodology in Goyal et al. (2024), I obtain an out-of-sample R^2 of 11.4%. A market timing strategy based on aggregate capital investment and cash savings outperforms a buy-and-hold strategy, yielding excess annual returns of 2.55%. Moreover, across 22 out of the 25 markets examined, aggregate cash savings negatively predict future market returns, with 12 of these markets showing statistically significant relationships. These stock markets include some of the largest in the world, such as China, France, Germany, Hong Kong, Singapore, Taiwan, and Switzerland. Further evidence reveals that in the U.S. market, this strong correlation also persists at both the size portfolio and individual firm levels, which implies that the return predictive power of aggregate cash savings primarily stems from the aggregation of their time-series predictive ability at the firm level.

The cash item under study (i.e., CHE in Compustat) includes cash, cash equivalents, and short-term investments, with the latter category potentially containing risky financial assets. The motivations for holding risk-free versus risky financial assets may differ substantially (Duchin et al., 2017). To shed light on this distinction, I perform a decomposition analysis, revealing that the covariance between cash savings and future market returns is primarily driven by firms' business-related, risk-free asset investments. Specifically, I decompose changes in cash holdings into operating cash flows, operating asset investing cash flows, financial asset investing cash flows, financing cash flows, exchange rate effects, short-term investments, and changes in restricted cash, and then compute the individual covariances of each component with future excess market returns. The components associated with financial asset investing cash flows and short-term investments, which could contain risky assets, together account for a negligible -7% of the total predictive power. In contrast, the combined

[1]This level of predictive power is comparable to the strength of aggregate short interest, which is one of the strongest predictors of market returns according to Rapach et al. (2016). Aggregate cash savings also exhibit better in-sample predictive performance compared to aggregate investment. Regressing future gross market returns on aggregate cash savings yields an adjusted R^2 of 16.7%, substantially exceeding the 10.4% reported for aggregate investment in Arif and Lee (2014). Throughout the analysis, aggregate savings are measured as the capitalization-weighted cross-sectional average of cash changes. It is also worth noting that aggregate cash levels do not predict future market returns, and the return predictive power of the cash change measure remains robust when using lagged total assets as weights, as shown in the online appendix.

contribution of operating cash flows, operating asset investing cash flows, and financing cash flows accounts for nearly 100% of the predictive power.

I further show that economic uncertainty is an important driver of this cash-return relationship through firms' business-related, risk-free investment behavior. Using cross-sectional return dispersion as an empirical proxy for uncertainty (e.g., Bloom, 2014; Herskovic et al., 2023), I find that this measure explains between 10% and 25% of the return forecasting power of cash savings across portfolio-level tests constructed under various sorting criteria.[2] A decomposition of the covariance between return dispersion and cash changes reveals that uncertainty predominantly affects cash flows related to business operations. Specifically, the net contribution from financial asset investments is only 18% of the total, while the combined impact of operating cash flows, operating asset investing cash flows, and financing cash flows amounts to 78%. Finally, I document cross-sectional heterogeneity in the return predictive power of cash savings. Theoretically, firms with higher R&D intensity or lower BM ratios are more likely to raise external funds and thus place greater value on potential future financing cost savings when managing cash holdings. Since uncertainty alters the value of these cost savings, cash holdings among these firms are more sensitive to uncertainty and carry stronger signals about future stock returns. I present evidence consistent with these predictions.

Given these empirical findings, I develop a neoclassical production-based asset pricing model, extending Eisfeldt and Muir (2016), to theoretically explore the link between cash savings, economic uncertainty, and future equity premia. In this framework, firms are heterogeneous with respect to idiosyncratic productivity and are exposed to aggregate productivity as well as economic uncertainty. Shocks to uncertainty increase the volatility of firm-level productivity. The model also incorporates firm exit and entry, following Begenau and Palazzo (2021), and allows for a time-varying price of risk as in Belo et al. (2023). Each period, firms face an exogenous probability of exit, with the exiting firms replaced by a mass of heterogeneous new entrants. Increased economic uncertainty, by reducing the price of risk,

[2] I choose price-based measures because productivity-based measures reflect past economic conditions and have limited predictive power for future stock returns.

lowers firms' exposure to aggregate productivity shocks. This modeling choice, in which risk aversion decreases as uncertainty rises, is intended as a reduced-form representation to match the empirical observation that stock return dispersion negatively predicts future equity premia (e.g., Angelidis et al., 2015; Maio, 2016). One possible explanation is that periods of high uncertainty create greater income dispersion among households (Herskovic et al., 2016), which, according to the habit persistence theory of Campbell and Cochrane (1999), leads to a dispersion of individual risk aversion. Since asset demand is a convex function of risk aversion, such risk aversion dispersion increases aggregate asset demand and thus reduces the effective risk aversion of a representative investor. Within this setting, firms make intertemporal decisions regarding capital investment and cash savings. Capital investment faces convex adjustment costs, and external financing incurs additional pecuniary costs. Holding cash enables firms to reduce financing costs, but imposes an opportunity cost due to lower returns on cash reserves.

An increase in economic uncertainty raises corporate cash savings through two primary channels and influences future equity premia mainly through changes in the price of risk. First, higher uncertainty leads to greater productivity variance, which increases the likelihood of future investment opportunities. As a result, firms anticipate a greater need for external financing and accumulate cash as a precaution to avoid possible future financing costs. This motive reflects the option value of holding cash. Second, elevated uncertainty reduces the price of risk and lowers the perceived riskiness of future financing cost savings. Regarding future equity premia, although uncertainty also endogenously affects firms' cash-to-capital ratios and the sensitivity of their equity returns to aggregate productivity shocks, model simulations indicate that the dominant way uncertainty influences future equity premia is via changes in the price of risk. In summary, heightened economic uncertainty tends to increase cash accumulation while simultaneously lowering expected equity premia, resulting in a negative association between corporate cash savings and subsequent stock market returns.

I calibrate the model to match key empirical moments. The calibrated model generates a sizable negative correlation between changes in cash holdings and subsequent equity premia. Beyond these targeted moments, the model yields several untargeted implications consistent with the data. It implies a positive correlation between cash savings and return dispersion, and a negative correlation between return dispersion and future market returns. Additionally, the model replicates the empirical finding that financing cash flows are the primary component driving the covariances between cash savings and both returns and dispersion, while investing cash flows contribute negatively. Finally, the model also reproduces the concentration of the return predictive power of cash savings among low-BM firms.

I further investigate the key structural features of the model that enable it to replicate the return predictive power of cash savings. To this end, I compare the model-implied moments under alternative specifications to those generated by the baseline calibration. While the model remains robust to variations in capital adjustment costs and variable financing costs, three elements prove essential: fixed financing costs, a time-varying price of risk, and firm exit. Fixed financing costs incentivize firms to maintain economically meaningful levels of cash. The time-varying price of risk serves as the critical mechanism linking economic uncertainty to future excess returns. The role of firm exit is particularly novel and has received limited attention in the prior literature. I show that while shutting down firm exit has little impact on the correlation between return dispersion and future equity premia, it substantially weakens the correlation between cash changes and return dispersion. Intuitively, the possibility of exit makes firms more cautious in responding to uncertainty shocks. Concerned about potential liquidation losses, firms slow their capital investment and prolong their cash holding periods. In contrast, absent firm exit, firms adjust cash holdings more aggressively and in a manner that is misaligned with the slower resolution of uncertainty. This disconnect weakens the positive association between cash changes and uncertainty, thereby diminishing the negative correlation between cash changes and future returns.

These findings also provide insights into the aggregate accruals puzzle. Given that firms tend to accumulate more cash during uncertain periods by liquidating net working capital (Kim, 2021), there exists a close relationship between cash savings and net working capital investment, the latter of which is a significant component of accruals. Hirshleifer et al. (2009)

show a positive correlation between accruals and future market returns at the aggregate level, while Sloan (1996) observes a negative correlation in the cross-section. Various explanations have been proposed to reconcile the puzzling aggregate results, including conditional equity premia, systematic earnings management, and merger and acquisition activity (Guo and Jiang, 2011; Kang et al., 2010; Heater et al., 2021). However, this paper reveals that after controlling for aggregate cash savings and capital investment, aggregate accruals have a negligible relation with future aggregate returns. This is because aggregate accruals, typically calculated as net working capital investment minus depreciation and amortization, incorporate parts of the predictive power found in both aggregate cash savings and investment. Cash changes exhibit a strong negative correlation with net working capital investment, whereas capital investment shows a strong positive correlation with depreciation and amortization. Consequently, the predictive power of aggregate accruals stems from a combination of these two factors but does not entirely capture their individual forecasting abilities.

Related literature. Although there are several papers investigating the cross-sectional return predictive power of corporate cash savings (e.g., Simutin, 2010; Palazzo, 2012; Sodjahin, 2013), studies examining its predictive power at the aggregate level are rare. The *cross-sectional* predictive power of an indicator does not necessarily imply the same predictor has *time-series* predictive power at the aggregate level (Maio and Santa-Clara, 2012). Importantly, I find that the cash-related measures in Palazzo (2012) and Sodjahin (2013) which have been shown to positively predict cross-sectional returns, actually exhibit a significantly negative association with future aggregate equity premia over time. This negative relationship, while similar, is less pronounced compared to the predictive power exhibited by the cash measure I propose. Instead, this paper is more closely related to the asset pricing literature that links aggregate firm investment decisions with stock market outcomes (e.g., Cochrane, 1991; Jones and Tuzel, 2013; Arif and Lee, 2014; Li et al., 2021; Belo et al., 2023). Complementing the role of capital investment in this context, this paper provides robust U.S. and International evidence demonstrating that aggregate corporate savings are a strong predictor of future market returns. I also quantitatively investigate this predictive power through the lens of a neoclassical dynamic model. This relates to other production-based asset pricing studies that incorporate uncertainty shocks (e.g., Segal, 2019; Basu et al., 2021; Herskovic et al., 2023; Segal and Shaliastovich, 2023).

I also contribute to the extensive literature examining the determinants of corporate cash holdings. Previous studies have attributed cash changes to factors such as cash flow risks (e.g., Bates et al., 2009; Riddick and Whited, 2009; Bolton et al., 2011; Begenau and Palazzo, 2021), access to external finance (e.g., Eisfeldt and Muir, 2016; Falato et al., 2022), competition intensity (e.g., Lyandres and Palazzo, 2016), corporate governance (e.g., Harford et al., 2008; Chen et al., 2012), repatriation tax costs (e.g., Hanlon et al., 2015), and more. I demonstrate that at the economy level, changes in discount rates resulting from fluctuations in economic uncertainty represent another significant source of cash savings waves.

Finally, this paper complements the aggregate accruals literature (Hirshleifer et al., 2009; Guo and Jiang, 2011; Kang et al., 2010; Heater et al., 2021) by proposing an alternative explanation for the puzzle. The findings indicate that the return predictive power of aggregate accruals can be subsumed by aggregate cash savings and aggregate capital investment. Thus, rather than attributing the positive correlation between aggregate accruals and future market returns to earnings management, the evidence supports a risk-based explanation.

The rest of the paper is organized as follows. Section 2 reports the empirical facts. Section 3 develops the model and presents the quantitative results. Section 4 discusses the empirical implications, and Section 5 concludes.

2 Empirical Analysis

2.1 Data and Sample Description

The primary dataset consists of annual U.S. firm-level financial information from Compustat and stock return data from CRSP. The sample period spans from 1964 to 2020. Macroeconomic data are obtained from the St. Louis Fed FRED database. Variable definitions are provided in Appendix A.1. Sample construction and variable calculation follow

Guo and Jiang (2011). Specifically, the sample includes non-financial firms with December fiscal year-ends and common equity listed on the NYSE, AMEX, or NASDAQ. To enable a meaningful comparison between aggregate accruals and aggregate cash savings, I require that firms used to compute aggregate cash savings also have non-missing accrual data. Firm-level accruals are measured as the change in non-cash current assets minus the change in current liabilities (excluding changes in short-term debt and taxes payable), less depreciation and amortization expense. Both cash changes and accruals are scaled by total assets at the beginning of the year. To mitigate the influence of outliers on aggregate variables, observations with the top and bottom 0.5% of scaled accruals and cash changes are trimmed each year.

For future market returns in year $t+1$, I use CRSP value-weighted index excess returns from May of year $t+1$ through April of year $t+2$. Because aggregate return predictability arises from the aggregation of firm-level predictability, I compute aggregate cash savings in year t using similar capitalization weights as future market returns in year $t+1$. Specifically, aggregate cash savings are calculated as the cross-sectional average of scaled cash changes, weighted by market capitalization at the end of year t. This weighting approach is consistent with Hirshleifer et al. (2009) and Guo and Jiang (2011). In tests examining the determinants of aggregate cash savings, I instead use beginning-of-year capitalization weights to avoid potential distortions from uncertainty-driven changes in firm size. Despite the weight choice difference, these two methods yield quantitatively similar results. Given that productivity-based measures of economic uncertainty primarily reflect historical conditions and have limited predictive power for future returns, I adopt a price-based measure used in Bloom (2009). Specifically, this measure is calculated as the cross-sectional size-weighted standard deviation of firm-level stock returns within a given year. As shown in Table 1, economic uncertainty is roughly twice as large as the standard deviation of excess market returns. Aggregate cash changes are predominantly positive throughout the sample period, consistent with the well-documented secular trend of rising corporate cash holdings.

International data on firm-level financials and stock prices are collected from Compustat Global. Compustat Global offers financial data starting from 1987, and has a wider coverage of large listed companies compared to other international accounting databases (as noted by Dai, 2012). For risk-free rates, I use the short-term monetary market rates from the OECD and the IMF International Financial Statistics databases. In cases where there are missing observations, I conduct cross-checks and obtain the necessary data from the respective central bank in each market. Annual risk-free rates are computed by compounding monthly rates. To ensure consistency, I convert historical firm-level financials and prices into the most recent currency used in each market.[3] Additionally, I exclude firms that are traded in foreign exchanges or in foreign currencies, because the focus of this study is to examine the impact of economic uncertainty on domestic firms and investors. I also keep markets with at least 18 consecutive years that have annual firm observations no less than 60. The final sample consists of 25 markets, encompassing both developed and developing economies. I contrast aggregate cash savings with future excess sample returns. Future excess market returns are calculated as the capitalization-weighted average of firm-level excess stock returns from May of year t through April of year $t+1$. To calculate aggregate cash savings, I trim the top and the bottom 2.5% observations in each year. This is necessary because in many market-years, the total number of observations is less than 100, rendering the previous 0.5% criteria ineffective in the trimming process. Aside from these differences, I apply the same methodology in computing aggregate variables as in the U.S. sample.

2.2 Motivating Facts

Since the 1960s, there has been a strong and negative time-series correlation between aggregate corporate cash savings and future excess market returns in the U.S. corporate sector, as illustrated in Figure 1. The aggregate cash savings variable demonstrates a statistically significant correlation of -0.39 with future excess market returns, which corresponds to an in-sample adjusted R^2 of 13.9%. In principle, this negative association could stem from the

[3]This currency conversion process is applied specifically to the European countries. Many companies in the European Union member-states adopting the Euro changed their reporting currency to the Euro during the sample period. As early as 1979, the European Economic Community used the European Currency Unit (ECU) as a unit of account to price some international financial transactions and capital transfers. As the Euro replaced the ECU at parity in 1999, the early exchange rate data about the ECU allow me to translate former member currencies into the same currency.

economic uncertainty examined in this study or from other determinants of cash savings. Two prominent factors documented in the literature are cash flow risk (e.g., Riddick and Whited, 2009) and time variation in external financing costs (e.g., Eisfeldt and Muir, 2016).

However, it is unlikely that the cash flow risk in productivity levels and financing cost variation are the primary drivers of the observed predictive power of cash. Unlike aggregate investment, which typically exhibits positive co-movement with business cycles (e.g., Arif and Lee, 2014), the aggregate cash savings depicted in Figure 1 do not display a strong cyclical pattern. During recessions, cash savings do not consistently rise or fall, and neither their peaks nor troughs are aligned with recession periods. This lack of systematic cyclical behavior suggests that, at the aggregate level, firms do not hold cash primarily due to current fewer investment opportunities (i.e., lower aggregate productivity level), thereby weakening the case for a productivity-level risk explanation. Variation in financing costs is also unlikely to be the dominant mechanism. In untabulated analyses using the equity issuance cost shock measure from Belo et al. (2019), I find that this variable has limited explanatory power for aggregate cash savings and weakly predicts future excess market returns, particularly when more recent data are included.[4]

In conclusion, the evidence suggests that neither productivity-level risk nor financing cost variation fully accounts for the cash-return relation. Motivated by the literature on precautionary corporate savings, I instead investigate how the cash flow risk in productivity variances affects firms' cash saving decisions and their implications for future stock returns.

2.3 Aggregate Cash Savings and Future Market Returns

2.3.1 Aggregate, Disaggregate and Global Evidence

I begin this section by examining whether aggregate cash savings predict future stock returns beyond standard predictors. Then I investigate the source of this predictive power

[4]The equity issuance cost shock (equity ICS) measures time variation in aggregate equity financing costs, with higher values indicating lower issuance costs. Although equity ICS has a positive price of risk and performs well in explaining cross-sectional stock returns in Belo et al. (2019), it demonstrates weak performance in forecasting future market returns at the aggregate level.

at more granular levels and conclude with international evidence to address potential small-sample concerns associated with the U.S. data.

Following the empirical specification in Arif and Lee (2014), I regress future excess market returns ($ExMkRet_t$) and future equal-weighted average excess returns ($ExSmRet_t$) on their respective capital- or equal-weighted aggregate cash savings at an annual frequency. The regressions also control for several known return predictors: the treasury term premium, the corporate bond default premium, the equity share of total new equity and debt issuance, the aggregate earnings-to-price ratio, the aggregate dividend yield, and the aggregate book-to-market ratio. As shown in Table 2 Panel A, both capital-weighted and equal-weighted aggregate cash savings significantly and negatively predict their respective capital- or equal-weighted excess future market returns. These findings suggest that the predictive power of cash savings is not confined to large firms and is not fully captured by traditional discount-rate proxies or valuation multiples.

Next, I explore the origins of this predictive power at disaggregate levels. Table 2 Panel B shows that the negative correlation between cash savings and future returns holds across both size portfolios and individual firms. This suggests that the predictive power of aggregate cash savings is simply the result of aggregating the time-series predictive power observed at the firm level. It does not arise from a subset of firms increasing their cash holdings while other firms experience a decrease in returns.

To quantify the extent to which the predictive power of aggregate cash savings reflects the aggregation of portfolio-level return predictability, I conduct a covariance decomposition exercise. Specifically, I decompose the covariance between aggregate cash changes and future market returns, $\text{Cov}(ChgCash_{t-1}, ExMkRet_t)$, into within- and cross-portfolio components across five size portfolios using fixed portfolio weights:

$$\text{Cov}(ChgCash_{t-1}, ExMkRet_t) =$$
$$\sum_{i=1}^{5} \bar{\omega}_i^2 \text{Cov}(ChgCash_{i,t-1}, ExRet_{i,t}) + \sum_{i=1}^{5} \sum_{j \neq i} \bar{\omega}_i \bar{\omega}_j \text{Cov}(ChgCash_{i,t-1}, ExRet_{j,t})$$

where $\bar{\omega}_i$ is calculated as the average of the capitalization weights for size portfolio i over time. The first term on the right-hand side represents within-portfolio covariance, while the second term captures cross-portfolio covariance. I find that the within-portfolio covariance accounts for the majority (71.3%) of the total. This evidence lends support to the idea that the time-series predictive strength of cash savings in the aggregate primarily stems from the time-series predictive power of cash at the disaggregate level.

To address the small sample size issue with the U.S. data, Table 3 provides global evidence using a similar design by regressing future excess market returns on aggregate cash savings for each market. In 22 out of the 25 markets that meet the sample selection criteria, aggregate cash savings have a negative impact on future excess sample aggregate returns, with 12 of these cases being statistically significant. These include some of the world's largest stock markets, such as China, France, Germany, Hong Kong, Singapore, Taiwan and Switzerland. Importantly, no market exhibits a significantly positive relationship between aggregate cash savings and future returns. To assess the overall predictive strength across countries, I calculate the cross-sectional average of estimated coefficients and also re-estimate the coefficient in a pooled regression with market fixed effects. Both approaches yield consistent results. The average coefficient implies that a 1% increase in aggregate cash savings forecasts a 2.2% decline in future excess market returns, comparable to the 2.6% estimate based on U.S. data.

Taken together, these findings provide robust and consistent evidence, both domestically and internationally, that aggregate corporate cash savings are a powerful predictor of future equity premia.

2.3.2 Comparison with Cross-Sectional Predictors

The ICAPM theory suggests a potential link between the cross-sectional and aggregate time-series predictive capabilities of a state variable. As per Merton (1973), innovations in these state variables that forecast future aggregate stock returns should be priced factors in the cross-section. Several studies have examined the predictive power of cash savings in the cross-sectional context. While I primarily emphasize the time-series predictive power, it's essential to consider how this predictive power might be mechanically related to the time-series predictive power of existing cross-sectional predictors as implied by the ICAPM theory. To address this, I aggregate several related characteristic measures and compare their predictive ability with aggregate corporate savings. Specifically, one can re-write the corporate savings ratio as follows:

$$\frac{Cash_{t-1} - Cash_{t-2}}{Asset_{t-2}} = \frac{Cash_{t-1}}{Asset_{t-1}} \times \frac{Asset_{t-1}}{Asset_{t-2}} \times \frac{Cash_{t-1} - Cash_{t-2}}{Cash_{t-1}}$$

In the cross-section, Palazzo (2012) finds that $Cash_{t-1}/Asset_{t-1}$ positively predicts future returns. The second ratio in the decomposition relates to the investment-to-asset ratio, $(Asset_{t-1} - Asset_{t-2})/Asset_{t-2}$, which exhibits a negative association with future stock returns according to Hou et al. (2015). The third relates to the change in the cash ratio, $Cash_{t-1}/Asset_{t-1} - Cash_{t-2}/Asset_{t-2}$, and it demonstrates a positive association with future stock returns as documented by Sodjahin (2013).

However, in contrast to the positive association between cash savings and future returns in the cross-section, Table 4 Columns 1 and 3 suggest that cash-related cross-sectional predictors significantly negatively correlate with future excess market returns in the aggregate. This inconsistency is not surprising as many cross-sectional predictors fail to forecast aggregate stock returns suggested by Maio and Santa-Clara (2012). In addition, the coefficient sign of the investment-to-asset ratio in Column 2 aligns with the cross-sectional results. In Columns 4-6, I compare the return predictive power of aggregate corporate savings with these aggregate cross-sectional predictors. Even after controlling for cross-sectional predictors, the forecasting power of aggregate corporate savings remains significant. This suggests that the forecasting ability of aggregate corporate savings is not solely attributable to the time-series predictive power of existing cross-sectional predictors.[5]

[5]In the online appendix, I run several tests to investigate the cross-sectional return predictive power of cash changes and compare it with related predictors. I find that cash changes negatively predict future returns at the cross-section, but this predictive power is relatively weak and trading on value-weighted cash change portfolios cannot provide significant returns. Additionally, the investment-to-asset ratio subsumes

2.3.3 Sources of the Return Predictive Power

To investigate the sources of the return predictive power in aggregate cash savings, I conduct a decomposition exercise based on accounting equivalence. As shown in Duchin et al. (2017), the Compustat cash measure (item CHE) used in this study includes both safe and risky financial assets. These components are conceptually distinct and have different implications for modeling firms' cash-saving incentives. However, disentangling the safe and risky portions of CHE is challenging, as firms do not consistently reconcile their financial asset disclosures with balance sheet accounts. To address this issue, I take an alternative approach by linking information from the cash flow statements to the balance sheets, thereby identifying the specific cash flow components that drive the return predictive power of changes in CHE.

Specifically, I decompose cash savings using the notations from Compustat as follows:

$$\begin{aligned}\Delta CHE_{t-1} = &\underbrace{OANCF_{t-1} + INVCF_{t-1} + FINCF_{t-1} + EXRE_{t-1}}_{=CHECH_{t-1}} \\ &+ \Delta INVST_{t-1} - \Delta RSTCHE_{t-1}\end{aligned}$$

where $INVST_{t-1}$ is short-term investments; $OANCF_{t-1}$, $INVCF_{t-1}$ and $FINCF_{t-1}$ are net cash flows from operating, investing and financing activities, respectively; $EXRE_{t-1}$ is the exchange rate effect; $CHECH_{t-1}$ is the change in cash, cash equivalents and restricted cash reported in cash flow statements; and $RSTCHE_{t-1}$ is restricted cash.

This identity holds because M&A-related cash outflows, recorded in investing cash flows, are reported net of acquired cash. Thus, M&A activity does not affect the difference between the cash change calculated from the balance sheet (ΔCHE_{t-1}) and the reported cash change in the statement of cash flows ($CHECH_{t-1}$). Due to frequent missing values for restricted cash, I approximate $\Delta RSTCHE_{t-1}$ as the residual between ΔCHE_{t-1} and the sum of the five observable components on the right-hand side. Furthermore, I decompose $INVCF_{t-1}$

the forecasting power of cash savings. The disparate findings at the aggregate and in the cross-section underscore that the predictive capabilities of cash savings in these contexts are distinct subjects of study.

into operating asset investing outflows ($-AQC_{t-1} - CAPX_{t-1} + SPPE_{t-1}$) and financial asset investing outflows, with the latter category consisting of both short-term and long-term financial asset investments. The decomposition of cash changes requires non-missing data for $OANCF_{t-1}$, $INVCF_{t-1}$, AQC_{t-1}, $CAPX_{t-1}$, $SPPE_{t-1}$, $FINCF_{t-1}$, $EXRE_{t-1}$, and $INVST_{t-1}$, restricting the analysis to the period from 1988 to 2020 with an average of 1,153 firms per year.

Despite the sample change, Table 5 confirms that aggregate cash savings continue to exhibit strong negative predictive power for future returns. The return covariance decomposition reveals that this power is primarily driven by firms' business operations, rather than by risky financial asset investments. Risky financial asset investments are classified under short-term investments and financial asset investing outflows, while the remaining components pertain to risk-free investments. While short-term investments account for 43% of the covariance between cash savings and future returns, cash outflows for financial asset investments contribute negatively at -50%, resulting in a negligible net effect of -7%. This is because an increase in short-term investments is mechanically offset by a decrease in investing cash flows. The main contributors are operating cash flows (17%), operating asset investing outflows (-48%), and financing cash flows (131%) — all linked to core business operations — whose combined contributions sum to approximately 100%. The negative contribution of operating asset investing cash flows means that they positively associates with future equity premia. As cash flows become more negative as investment increases, this implies that capital investment negatively associates with future equity premia, consistent with prior research. Moreover, the negative contribution from operating asset investing cash flows suggests that incorporating capital investment may enhance the return predictability of cash savings, a possibility explored in out-of-sample tests reported in the online appendix.

In summary, the evidence indicates that the predictive power of aggregate cash savings for future excess market returns is primarily driven by financing activity, with operating asset investing outflows exerting a counteracting negative contribution.

2.4 The Role of Economic Uncertainty

Having established that aggregate cash savings negatively predict future market returns, I now examine the role of economic uncertainty in shaping this predictive relationship. I begin by analyzing whether economic uncertainty explains the overall predictive power of cash savings. I then assess the relative predictive power of cash among firms that are likely to be more sensitive to fluctuations in economic uncertainty.

2.4.1 Explanatory Power of Economic Uncertainty

In analyzing the determinants of cash savings, I regress portfolio- and aggregate-level cash savings on the measure of economic uncertainty, incorporating a linear time trend to control for secular patterns following Guo and Jiang (2011). A valid proxy for economic uncertainty should both predict future excess market returns and explain variation in aggregate corporate cash savings, thereby accounting for the return predictability of cash. Accordingly, I choose a price-based measure, stock return dispersion, as a proxy for economic uncertainty. Table 6 Panel A Columns 1-5 report a consistent and positive relationship between return dispersion and cash changes across all size quintiles. At the aggregate level in Column 6, return dispersion explains approximately 10% of the variation in cash changes. These results highlight the significant explanatory power of economic uncertainty for corporate cash savings at both the portfolio and aggregate levels.

The strong correlation between cash savings and economic uncertainty raises the question of how cash savings perform in predicting future returns in the presence of economic uncertainty. I assess the explanatory power of uncertainty at the portfolio level while controlling for portfolio fixed effects. This portfolio-level analysis is motivated by three considerations. First, standard firm-year panel regressions with firm fixed effects do not adequately address the issue of asset migration. Firms evolve over time, shifting across size, value, and investment categories, and firm fixed effects fail to capture such dynamic transitions. Second, since economic uncertainty exhibits only time-series variation and cannot explain cross-sectional return differences, using firm-year panel regressions risks introducing downward bias in the explanatory power of economic uncertainty. Third, by conducting tests at the portfolio level as opposed to the aggregate level, I can expand the sample size, thereby improving the precision and reliability of the estimates.

Specifically, I sort observations in each year into terciles based on the Fama-French ten industries, market capitalization, book-to-market ratio or investment-to-asset ratio, and aggregate firm-level cash savings and future excess stock returns within these portfolios. Next, I regress future excess portfolio returns on portfolio-level cash changes, both with and without controlling for return dispersion. The estimated coefficients of cash savings are reported in Table 6 Panel B. The results show that, across all specifications without return dispersion, portfolio-level cash savings significantly predict future excess returns. However, after including return dispersion as a control, the coefficients on $ChgCash_{i,t-1}$ decline significantly by 10% to 25% in magnitude. That economic uncertainty does not fully explain the predictive power of cash savings may reflect several possibilities: a direct effect of cash on future returns, return dispersion being an imperfect proxy for uncertainty, misspecification of the underlying functional form, or the influence of other omitted variables. This finding is consistent with Li et al. (2021), who document that proxies for economic uncertainty also do not fully account for the return predictability of expected investment growth.

To further explore the link between economic uncertainty and cash savings, I decompose the covariance between return dispersion and aggregate cash changes into the covariances between return dispersion and the individual components of cash flows, mirroring the decomposition for return predictability. Table 5 shows that the impact of return dispersion is primarily attributable to firms' operating activities as well. Specifically, the net impact of financial asset investments is 18% (i.e., 49% minus 31%), which is much smaller compared to the 78% contribution from business operations (i.e., 48% minus 70% plus 100%).[6]

To sum up, these results show that economic uncertainty explains the return predictive power of cash savings, and it affects aggregate cash savings mostly through firms' business

[6]That investing cash outflows negatively associated with return dispersion appears to contradict the theoretical prediction in Bloom (2009), who shows that capital investment should decline in response to productivity-based uncertainty shocks. This discrepancy is discussed in detail in Section 3.3.3.

operation activities. These results motivate me to incorporate an uncertainty shock into the neoclassical dynamic model developed in the following section.

2.4.2 Heterogeneity in the Cash-Return Relation

While cash changes may be influenced by various factors beyond uncertainty, leading to ambiguity in their relationship with future returns, the previously established negative correlation under uncertainty-driven scenarios suggests a testable implication: firms more sensitive to uncertainty shocks should exhibit a stronger predictive relation between their cash savings and subsequent returns. That is, higher uncertainty sensitivity strengthens the cash-return linkage. I hypothesize that this sensitivity is particularly pronounced among firms with greater R&D intensity and lower book-to-market ratios.

Firms' cash holding decisions are closely tied to anticipated external financing needs, as demonstrated by Eisfeldt and Muir (2016). In my context, uncertainty affects cash savings through firms' valuation about future financing cost savings. This gives rise to two important implications. First, firms facing greater external financing needs tend to accumulate more cash. For R&D-intensive firms, because of their lower profitability, higher growth potential and more financing constraints, they are found to hoard more cash and are responsible for the secular trend of increasing cash holdings since the 1980s (e.g., Begenau and Palazzo, 2021; Falato et al., 2022). Similarly, firms with lower BM ratios (i.e., growth firms) also hold more cash due to their higher investment likelihood according to Palazzo (2012). Second, this greater reliance on external financing makes such firms more vulnerable to uncertainty shocks that affect the expected value of future financing cost savings. Consequently, I expect that the cash savings of R&D-intensive and growth firms are more strongly associated with future excess stock returns.[7]

To test these hypotheses, I sort firms into quintiles based on two dimensions: the R&D intensity of the sectors they belong to, as in Begenau and Palazzo (2021), and their demeaned BM ratios. The sector-based R&D classification is necessary due to the limited availability

[7]The prediction for growth firms is also supported by the model. See Section 3.3.2 for details.

of R&D expenditure disclosures in earlier years. I categorize SIC three-digit industries into quintiles based on their historical average R&D investment as a percentage of total assets since 1964. To account for the difference between R&D and non-R&D firms, in each year, a firm's BM ratio is demeaned using the average BM ratio within its respective group, either the top R&D quintile or one of the remaining four non-R&D quintiles. I then compute portfolio-level cash savings and future excess returns for each quintile and run time-series regressions. Table 7 Panel A shows that cash savings significantly predict future returns in the most R&D-intensive quintile, while the predictive power is statistically insignificant in the other groups. Additionally, Panel B reveals that the return-predictive power of cash savings is much stronger for firms with low BM ratios, as reflected in both the larger coefficient magnitudes and the higher adjusted R^2 values in Columns 1 and 2.

Overall, these results underscore the central role of economic uncertainty in explaining cross-sectional heterogeneity in the return predictive power of corporate cash savings.

3 Quantitative Analysis

This section develops and calibrates a production-based asset pricing model to examine how economic uncertainty contributes to the return predictability of corporate cash savings.

3.1 Model

3.1.1 Model Setup

The model features heterogeneous firms that enter and exit exogenously in a partial equilibrium setting. Incumbent firms produce using capital and face quadratic capital adjustment costs. Firms can accumulate cash to mitigate pecuniary costs associated with external financing; however, cash holdings earn a return below the risk-free rate. Firm productivity consists of an aggregate and an idiosyncratic component, with the latter subject to stochastic volatility reflecting economic uncertainty. The stochastic discount factor is specified in a reduced form, with the price of risk declining with economic uncertainty.

Incumbent problem. Incumbent firms in the economy are price takers and use capital to produce a homogeneous product, the price of which is normalized to one. Each incumbent firm produces output according to:

$$Y_{it} = A_{it}^{1-\alpha} K_{it}^{\alpha}$$

in which $\alpha \in (0, 1]$ governs the degree of returns to scale, and A_{it} denotes firm-level total factor productivity. The law of motion for the firm capital is given by:

$$K_{i,t+1} = (1-\delta)K_{it} + I_{it}$$

where δ is the depreciation rate and I_{it} is firm i's capital investment at time t that entails a quadratic adjustment cost:[8]

$$\Theta(I_{it}, K_{it}) = \frac{1}{2}\theta \left(\frac{I_{it}}{K_{it}}\right)^2 K_{it}.$$

At time t, the firm chooses the amount of cash $L_{i,t+1}$ to carry over to the next period. The firm's pre-financing payout is given by internal cash flows net of capital investment plus liquidity accumulation:

$$E_{it} = Y_{it} - I_{it} - \Theta(I_{it}, K_{it}) + L_{it} - \frac{L_{i,t+1}}{1+r_s}$$

where $r_s = r_f(1-\tau)$ is the after-tax return on cash holdings, and r_f is the risk-free rate. The firm holds cash to avoid costly equity financing. If the firm has to issue equity, i.e., $E_{it} < 0$, it incurs financing costs following the specification in Eisfeldt and Muir (2016). The

[8] Following Eisfeldt and Muir (2016), the baseline specification assumes symmetric adjustment costs for simplicity. However, the results remain robust to the inclusion of asymmetric costs, as discussed later.

net payout to shareholders is

$$D_{it} = E_{it} - \left(\lambda_1 Z_{i,t-1} + \frac{1}{2} \lambda_2 \frac{E_{it}^2}{K_{it}} \right) \mathbb{I}_{E_{it}<0}$$

where $\lambda_1, \lambda_2 > 0$ govern the fixed and variable components of equity issuance costs, and $\mathbb{I}$ is an indicator function equal to one if $E_{it} < 0$. The fixed cost is scaled by the trend so that it does not become trivial along the balanced growth path.

I incorporate firm exit and entry into the model following Begenau and Palazzo (2021). Each period, the firm faces an exogenous probability of exit, denoted by $1 - \pi$.[9] The incumbent firm's value solves

$$V_{it} = \max_{K_{i,t+1}, L_{i,t+1}} D_{it} + \pi \mathbb{E}_t[M_{t+1} V_{i,t+1}] + (1 - \pi) \mathbb{E}_t \left[M_{t+1} \left(L_{i,t+1} + \phi J_{i,t+1} \right) \right]$$

where M_{t+1} is the stochastic discount factor from time t to $t+1$, and $\phi J_{i,t+1}$ represents the liquidation value of capital, with $\phi < 1$. Upon exit, the firm returns its accumulated cash and the liquidation value of its capital to investors. The value of installed capital, $J_{i,t+1}$, is given by the sum of discounted future output:

$$J_{it} = Y_{it} + \mathbb{E}_t \left[M_{t+1} J_{i,t+1} \right], \quad \text{s.t.} \quad K_{i,t+1} = (1 - \delta) K_{it}.$$

Entry problem. Each period, a constant mass $1 - \pi$ of incumbent firms exits the economy. This exiting mass is replaced by an identical mass of new entrants. While entry is exogenous, entrants choose their initial capital and cash holdings to maximize firm value upon entry. Specifically, each entrant draws an idiosyncratic productivity from the stationary cross-sectional distribution and, based on the expectation about future states, solves:

$$V_{it}^E = \max_{K_{i,t+1}, L_{i,t+1}} -K_{i,t+1} - \frac{L_{i,t+1}}{1 + r_s} + \pi \mathbb{E}_t \left[M_{t+1} V_{i,t+1} \right] + (1 - \pi) \mathbb{E}_t \left[M_{t+1} \left(L_{i,t+1} + \phi J_{i,t+1} \right) \right]$$

[9] Exit refers to delisting events such as privatization, acquisition, or failure to meet continued listing requirements. As noted by Begenau and Palazzo (2021), the average cash holdings of exiting firms are similar to those of surviving incumbents, supporting the assumption of exogenous exit.

Because entrants make their capital and cash decisions in the beginning of a period, consistent with the exit assumption for incumbents, they also face an exit probability of $1 - \pi$ at the end of this period.

Stochastic processes. Firms in the economy are subject to three exogenous shocks: idiosyncratic productivity, aggregate productivity, and economic uncertainty. Firm-level productivity A_{it} consists of an aggregate-level component X_t and an idiosyncratic component Z_t, such that $A_{it} = X_t Z_{it}$. The idiosyncratic productivity evolves according to:[10]

$$Z_{i,t+1} = Z_{it}\left(1 + \sigma_{zt}\epsilon_{zi,t+1}\right), \quad \epsilon_{zi,t+1} \sim \mathcal{N}(0,1)$$

where $\epsilon_{zi,t+1}$ is a firm-level i.i.d. productivity shock, and σ_{zt} is an aggregate-level uncertainty shock, which follows a two-state Markov process:

$$\sigma_{zt} \in \{\sigma_L, \sigma_H\}, \quad \text{where} \quad \mathbb{P}(\sigma_{z,t+1} = \sigma_j | \sigma_{zt} = \sigma_k) = \pi^{\sigma}_{kj}.$$

This specification, adopted from Bloom (2009), ensures that uncertainty shocks affect the conditional variance of future productivity, but not its conditional mean. In other words, $\mathbb{E}_t[Z_{i,t+1}] = Z_{it}$, allowing the analysis to isolate volatility effects.[11] Similarly, the aggregate productivity follows:

$$X_{t+1} = \bar{X}_t^{1-\rho_x} X_t^{\rho_x}\left(1 + \sigma_x \epsilon_{x,t+1}\right), \quad \epsilon_{x,t+1} \sim \mathcal{N}(0,1)$$

where $\rho_x < 1$, $\epsilon_{x,t+1}$ is an aggregate-level i.i.d. productivity shock, and σ_x is the conditional volatility of aggregate productivity. Here, ρ_x is set to be less than one so that X_{it} is stationary. In logs, this is equivalent to an AR(1) process.

[10] Similar to Ai et al. (2020), although the idiosyncratic process is non-stationary, the exogenous exit assumption ensures that firm size does not grow without bound.

[11] This can be more clearly seen from its conversion to logs: $\log(Z_{i,t+1}) = \log(Z_{it}) - \sigma^2_{zt}/2 + \sigma_{zt}\varepsilon_{zi,t+1}$, whereas in the standard AR(1) specification without adjusting $-\sigma^2_{zt}/2$, $\mathbb{E}_t[Z_{i,t+1}] = Z_{it}\exp(\sigma^2_{zt}/2)$. The expected value of $Z_{i,t+1}$ increases with economic uncertainty in an AR(1) process.

Stochastic discount factor. To focus on the production side of the economy, I directly specify the stochastic discount factor, abstracting from an explicit household optimization problem. The discount factor takes a log-linear form with time-varying risk aversion:

$$M_{t+1} = \beta \frac{\exp(-\gamma_t(x_{t+1} - x_t))}{\mathbb{E}_t[\exp(-\gamma_t(x_{t+1} - x_t))]}, \quad \gamma_t = \gamma - \gamma_z \sigma_{zt}^2$$

where $x_t = \log(X_t)$. γ_t is the risk aversion coefficient, which declines in economic uncertainty. The stochastic discount factor is demeaned by its conditional expectation so that the risk-free rate is constant, i.e., $1 + r_f = 1/\mathbb{E}_t[M_{t+1}] = 1/\beta$. This normalization allows the model to focus on risk premia as the key source of variation in asset prices.

This pricing kernel is akin to the one in Belo et al. (2023), except for its time-varying risk aversion decreasing with economic uncertainty ($\gamma_z > 0$), which is the focus of this paper. Similar to the exogenous risk aversion setup in Basu et al. (2021), this specification is reduced-form in nature and serves to align with the empirical findings that the proxy for economic uncertainty, stock return dispersion, negatively predicts future equity premia (e.g., Angelidis et al., 2015; Maio, 2016; Eiling et al., 2023). One potential rationale for this assumption is as follows. According to Herskovic et al. (2016), during times with high economic uncertainty, there is high dispersion in the distribution of individual household's income. Under the habit formation framework of Campbell and Cochrane (1999), individual risk aversion declines as wealth increases. As a result, dispersion in income induces heterogeneity in risk aversion across households. Given that asset demand is a convex function of risk aversion, greater dispersion in individual risk aversion raises aggregate asset demand, effectively reducing the representative investor's aggregate risk aversion during high-uncertainty periods.[12]

[12] Consider a market for a single risky asset. Suppose two investors have asset demand given by $\frac{x}{\rho_i}$, $i = 1, 2$, where $x = \frac{\mathbb{E}(V|I) - P}{\mathrm{Var}(V|I)}$, I is investors' information set, V is the actual asset value and P is the market price. If the both investors share the same risk aversion ρ, the total demand is $\frac{2x}{\rho}$, and the aggregate risk aversion of a representative investor is $\frac{1}{2}\rho$. However, if the investors have risk aversion at $\rho \pm a$, aggregate demand becomes $\frac{x}{\rho - a} + \frac{x}{\rho + a}$, and the implied aggregate risk aversion becomes $\frac{1}{2}\rho - \frac{a^2}{2\rho}$, holding asset price constant.

3.1.2 Cash Holding Decisions and Future Stock Returns

For notation simplicity, I suppress the firm index i in what follows. Given the incumbent firm maximization problem, a first-order approximation of the Euler equation for cash holdings L_{t+1} yields:

$$\varphi_{et} + r_f\tau = -\pi\gamma_t \mathrm{Cov}_t(\Delta x_{t+1}, \varphi_{e,t+1}) + \pi\mathbb{E}_t[\varphi_{e,t+1}] \tag{1}$$

where φ_{et} represents the shadow value of cash in excess of the value of payouts in the current period. Specifically, $\varphi_{et} = 0$ if $E_t > 0$; $\varphi_{et} = \hat{\varphi}_{et}$ if $E_t = 0$; and $\varphi_{et} = -\lambda_2 E_t/K_t$ if $E_t < 0$. As in Eisfeldt and Muir (2016), $\hat{\varphi}_{et}$ is the multiplier on the pseudo-constraint $E_t \geq 0$, introduced to account for the fixed cost associated with accessing external finance. The excess shadow value of internal cash increases when the firm is raising external finance or when it would prefer to do so but refrains due to fixed issuance costs.

In Equation 1, the left-hand side represents the marginal costs of cash holdings, which include the excess shadow value of current cash and the income tax paid on cash saving interest. The right-hand side captures the marginal benefits, consisting of the expected future excess cash value, $\mathbb{E}_t[\varphi_{e,t+1}]$, and the riskiness of this value, $\gamma_t \mathrm{Cov}_t(\Delta x_{t+1}, \varphi_{e,t+1})$. An increase in uncertainty raises cash through two channels. The first channel works through a higher future productivity variance, raising the likelihood of future investment and thereby increasing $\mathbb{E}_t[\varphi_{e,t+1}]$. This reflects the option value of cash balances (e.g., Riddick and Whited, 2009). In the second channel, heightened uncertainty reduces the price of risk, which lowers the riskiness of future cash value, making it more valuable from today's perspective.

I next examine how economic uncertainty affects expected stock returns. From the incumbent firm's Bellman equation, the expected excess return is given by:

$$\mathbb{E}_t r^e_{t+1} = \gamma_t \mathrm{Cov}_t\left(\Delta x_{t+1}, \underbrace{\frac{\pi V_{t+1} + (1-\pi)(L_{t+1} + \phi J_{t+1})}{V_t - D_t}}_{=R_{t+1}}\right) \tag{2}$$

where $r^e_{t+1} = r_{t+1} - r^f$, and $r_{t+1} = R_{t+1} - 1$ denotes the net return on the firm's equity.

According to Equation 2, the equilibrium risk premium is determined by the product of the time-varying price of risk, γ_t, and the conditional covariance between aggregate productivity growth and the firm's return. Given that firm continuation and liquidation values, V_{t+1} and J_{t+1}, typically rise with aggregate productivity, the covariance term is generally positive, implying that expected excess returns are on average positive. While examining the relationship between economic uncertainty and the endogenous covariance requires solving the model numerically, a direct implication of Equation 2 is that increases in economic uncertainty reduce the price of risk, thereby lowering expected excess returns.

3.2 Calibration

I calibrate the model at a monthly frequency and report the parameter values in Table 8. Details about the solution algorithms and the numerical implementation are included in the appendix. I simulate 4,000 firms for 1,120 months with the initial 400 months discarded. The remaining 720 months or 60 years are treated as those from the stochastic equilibrium. To ensure comparability between model-implied and empirical aggregate moments, I aggregate monthly simulated firm-level data over time and across firms in the same way as I process the real data.[13] I repeat this simulation 500 times and calculate the averages of the moments and their associated t-statistics across panels in Table 9. The calibration involves exogenously restricting the values of some parameters, while setting the remaining ones to replicate baseline empirical moments.

Firm technology. The parameters whose values are set ex-ante based on prior studies include capital share α, depreciation rate δ, recovery rate upon liquidation ϕ, continuation probability π, and income tax rate τ. α is set to 35%, consistent with values used in Belo et al. (2014) and Bloom (2009). The monthly depreciation rate δ implies an annual rate of 10%. The recovery rate ϕ is set to 0.85 to match the delisting returns of -15%, in line with the estimates in Bai et al. (2019) and Herskovic et al. (2023). The continuation probability

[13]Since firms are all-equity financed in the model, following Belo et al. (2014), I scale up all simulated returns by a factor of 1.67 to ensure comparability with the data.

is fixed at $\pi = 0.992$, implying an annual firm exit rate of approximately 9.6%, consistent with the delisting rate reported by Doidge et al. (2017). I calibrate the adjustment cost parameters $\{\theta, \lambda_1, \lambda_2\}$ to be $\{0.36, 0.04, 0.0004\}$ by targeting the average cash-to-asset ratio, as well as the mean and volatility of aggregate cash savings and aggregate investment rate. As shown in Table 9 Panel A, those model-implied moments closely match their empirical counterparts. These values are also broadly consistent with those estimated by Eisfeldt and Muir (2016) using the Simulated Method of Moments, who report calibrated values of $\{0.26, 0.16, 0.0004\}$.

Stochastic processes. In the stochastic discount factor, the time-preference coefficient is set to $\beta = 0.9985$, following Belo et al. (2014), which implies an annual real interest rate of 1.8%. Parameters related to productivity level shocks are set exogenously based on prior studies. Specifically, the persistence of log aggregate productivity is set to $\rho_x = 0.985$, following Herskovic et al. (2023), while the volatility of log aggregate productivity, $\sigma_x = 0.055$, is taken from Belo et al. (2014). The average level of log aggregate productivity, $\bar{x} = \log \bar{X}$, is set to ensure that the average simulated capital level equals one, as in Zhang (2005). For uncertainty shocks, the transition probabilities π^{σ}_{HL} and π^{σ}_{LH} are estimated from annual stock return dispersion data. Periods in which return dispersion exceeds its sample average are classified as high uncertainty, and those below as low uncertainty. The levels of uncertainty, σ_H and σ_L, along with the risk aversion parameters, are calibrated to match return-related moments, including the average level of return dispersion, the ratio of return dispersion in high- versus low-uncertainty states, the correlation between aggregate cash savings and future market returns, and the mean and volatility of excess market returns.

The estimated annual conditional transition probabilities are $\pi^{\sigma}_{HH} = 0.41$ and $\pi^{\sigma}_{LL} = 0.72$, which correspond to monthly values of $\pi^{\sigma}_{HH} = 0.92$ and $\pi^{\sigma}_{LL} = 0.97$. These transition probabilities are broadly consistent with those used in Bloom (2009). In particular, $\pi^{\sigma}_{LL} = 0.97$ implies $\pi^{\sigma}_{LH} = 0.03$, identical to Bloom (2009), and $\pi^{\sigma}_{HH} = 0.92$ corresponds to a half-life of approximately eight months for an uncertainty shock, closely aligning with the six-month half-life considered in that study. The calibration of σ_L and the ratio σ_H/σ_L

targets an average return dispersion of 0.35 and a high-to-low dispersion ratio of 1.74, which are reasonably close to the empirical values of 0.29 and 1.67, respectively. The resulting calibrated values, $\{\sigma_L, \sigma_H/\sigma_L\} = \{0.066, 2.2\}$, are also in line with the estimates in Bloom (2009), who report $\{0.17, 2.0\}$ under a specification with quadratic capital adjustment costs.

I calibrate the relative risk aversion coefficient to $\gamma = 14$ and the loading on economic uncertainty to $\gamma_z = 810$. As reported in Table 9 Panel A, the model slightly understates the volatility of market returns relative to the data. This discrepancy arises because the one-factor stochastic discount factor, without a countercyclical price of risk, cannot fully account for the observed return volatility.[14] Since this paper focuses on the role of economic uncertainty in shaping the price of risk, I do not assume a countercyclical price of risk to avoid parameter proliferation. Nevertheless, the discrepancy remains within a reasonable range, and the remaining model-implied return moments closely match their empirical counterparts.

3.3 Model Results

In this section, I first establish economic uncertainty as the key driver enabling the model to replicate observed aggregate moments, and discuss its cross-sectional implications. Next, I analyze the model-generated aggregate moments in detail by examining impulse responses to an uncertainty shock. Finally, I explore the underlying mechanism by evaluating the quantitative performance of alternative model specifications.

3.3.1 Sources of Aggregate Movements

Among the two aggregate shocks in the model, aggregate productivity and economic uncertainty, I find that the correlations among aggregate variables are primarily driven by uncertainty shocks. Moreover, uncertainty affects aggregate cash savings mainly by reducing investing cash flows and increasing financing cash flows, consistent with the data.

Table 9 Panel B, presents a comparison between model-implied aggregate moments and

[14]Most production-based asset pricing studies that use a one-factor discount factor adopt a countercyclical price of risk to generate sizable return volatility; see, for example, Zhang (2005), Belo et al. (2023), and Eiling et al. (2023).

their empirical counterparts. Although none of these moments were used as calibration targets, the model matches them well. Among unconditional moments, the model implies a positive correlation of 0.30 between cash savings and return dispersion, and a negative correlation of -0.32 between return dispersion and future market returns. These values are close to their empirical analogs, 0.33 and -0.25, respectively. To further disentangle the role of uncertainty shocks, I compute model-implied and empirical moments conditional on aggregate TFP. Specifically, in the data, I use the annual percentage change in TFP for the private business sector, as reported by the U.S. Bureau of Labor Statistics. I regress aggregate variables on this measure and compute correlations and covariances using the residuals from these regressions. In the model, as in the data, these conditional correlations are similar to their unconditional counterparts, highlighting the central role of uncertainty shocks in driving the observed unconditional aggregate moments. These results further suggest that heightened uncertainty increases return dispersion and cash savings while lowering future excess market returns.

Next, I revisit the decomposition analysis from the empirical section and assess whether the model can replicate the source-level breakdown of cash savings. In the model, I decompose cash savings into cash flows from different activities, following:

$$\frac{L_t}{1+r_s} - L_{t-1} = Y_{t-1} - I_{t-1} - \Theta_{t-1} - E_{t-1}$$

where operating cash flows are defined as Y_{t-1}, investing cash flows as $-I_{t-1} - \Theta_{t-1}$, and financing cash flows as $-E_{t-1}$, which represent equity issuance proceeds (i.e., $-D_{t-1}$) net of external financing costs. I follow the empirical methodology by deflating each component by beginning-of-period total assets and aggregating across firms.

For the data moments in Table 9 Panel B, I focus on operating, operating asset investing, and financing cash flows as reported in Table 5, and compute their percentage contributions conditional on aggregate TFP. The underlying mechanisms are discussed in greater detail in the impulse response analysis that follows. The results show that in both the model and the data, financing cash flows are the dominant contributor to both the conditional correlation between cash savings and future returns, and the correlation between cash savings and return dispersion. Investing cash flows contribute negatively, ranking second in magnitude. The model indicates a negative but insignificant contribution of operating cash flows, whereas their contribution is positive in the data. This discrepancy stems from the earlier modeling choice that mutes the mean effect of uncertainty shocks on productivity in the specification of the idiosyncratic TFP process. Overall, the results support the view that uncertainty shocks are a key driver of the observed aggregate moments.

3.3.2 Characteristics across BM Portfolios

The aforementioned empirical results show that the cash savings of firms with low book-to-market ratios exhibit stronger return predictive power. I now examine whether the model can replicate this empirical pattern.

Theoretically, growth firms are more likely to hold cash, as they tend to invest more in the future. This increases the probability of incurring external financing costs, raising the future excess value of internal funds, $\varphi_{e,t+1}$. Moreover, the exposure of cash savings to economic uncertainty also depends on this investment propensity. According to Equation 1, value firms typically have positive payouts, implying that $\varphi_{e,t+1}$ and thus $\mathrm{Cov}_t(\Delta x_{t+1}, \varphi_{e,t+1})$ are close to zero. As a result, fluctuations in the price of risk have limited impact on their marginal benefit of holding cash. Consequently, changes in cash savings are less informative about future returns for value firms than for growth firms. In contrast, growth firms with higher $\varphi_{e,t+1}$ have cash savings that are more sensitive to uncertainty shocks and thus more predictive of future returns.

In line with the empirical results discussed in Section 2.4.2, Table 9 Panel C reports the characteristics for the lowest and highest BM quintiles. These include the correlations between cash savings and future excess portfolio returns, $\mathrm{Corr}(ChgCash_{t-1}, ExRet_t)$, and between cash savings and return dispersion, $\mathrm{Corr}(ChgCash_{t-1}, RetDisp_{t-1})$; the sum of operating and financing cash flows, $CFO_{t-1} + CFF_{t-1}$; investing cash flows, CFI_{t-1}; and changes in cash holdings, $ChgCash_{t-1}$. I do not separately report operating and financing cash flows because most cash flow information is unavailable prior to 1988. As an alternative, for moments computed using data since 1964, I compute $CFO_{t-1}+CFF_{t-1} = ChgCash_{t-1}+CapInvt_{t-1}$, and $CFI_{t-1} = -CapInvt_{t-1}$. The corresponding moments in the model are computed by replicating these empirical procedures using the simulated data.

In Table 9 Panel C, the moments computed using data since 1964 or since 1988 are very similar, highlighting the robustness of these cross-sectional patterns. While the model overshoots the magnitudes of data moments reported in Column High-Low, particularly for $CFO_{t-1}+CFF_{t-1}$ and CFI_{t-1}, the signs and statistical significances are consistent with the data. As in the model and in the data, significantly negative values for CFI_{t-1} in Column High-Low indicate that growth firms have higher investment rates. These firms accumulate greater cash holdings through higher operating and financing flows, as can been seen in the $CFO_{t-1} + CFF_{t-1}$ and $ChgCash_{t-1}$ results. The higher cash levels for growth firms are consistent with the empirical findings in Palazzo (2012). The lower correlation between cash savings and future returns, and the higher correlation between cash savings and return dispersion for growth firms, are also consistent with the theoretical predictions discussed above. Taken together, these cross-sectional results suggest that the return predictive power of corporate cash savings is concentrated among growth firms, whose savings are more sensitive to economic uncertainty due to their higher propensity to invest.

3.3.3 Dynamic Responses

I next examine how uncertainty shocks generate the simulated aggregate correlations reported in Table 9. Specifically, I analyze how uncertainty shocks jointly affect changes in cash holdings, return dispersion, and the equity premium, as well as different cash flow components. This analysis entails studying the dynamic responses of key endogenous variables to a shock in economic uncertainty.

I simulate an economy of 4,000 firms over 18 quarters (54 months), using the baseline calibration of the model. In each simulation, the economy is hit by an uncertainty shock,

$\sigma_{zt} = \sigma_H$, at the beginning of quarter 1, while all other shocks are randomly drawn. This simulation is repeated 25,000 times. I compute the average responses of selected aggregate variables across simulations. These variables are computed using the same aggregation procedures described in the empirical section. The impulse responses, normalized to unity prior to the shock, are plotted on a quarterly basis in Figure 2.

Figure 2A shows that the uncertainty shock produces an immediate and sharp spike in σ_{zt} across simulations, and it decays rapidly with a half-life of roughly two to three quarters. The rise in σ_{zt} is less than 120% because some of the 25,000 simulations already have the high-uncertainty state. Importantly, the uncertainty shock does not affect the average productivity in the economy. Return dispersion increases sharply upon the shock and decays at the same rate, suggesting a strong positive correlation between uncertainty and return dispersion. Figure 2B plots the response of excess market returns. Returns rise immediately following the uncertainty shock and decline steadily over the next eight quarters. This initial increase occurs because the shock lowers the price of risk in the following period, rather than in the current one. As a result, future cash flows become less risky, which raises their present value and leads to an increase in firm valuation. As shown in Figure 2C, the uncertainty shock also induces a rise in aggregate cash savings, due to a decline in the price of risk and an increase in investment propensity according to Equation 1. The dynamics of aggregate cash savings mirror the paths of the uncertainty shock and return dispersion, reinforcing the simulated positive correlation between cash changes and return dispersion.

Figure 2D illustrates the responses of the cash flow components that contribute to cash changes. The magnitude of investing cash flows initially increases (i.e., becomes more negative) and reverts to pre-shock levels within four quarters. Meanwhile, financing cash flows decrease (i.e., become less negative) and return to baseline at a similar pace. The response of operating cash flows is negligible. Aggregate investing cash flows are negative before the shock. Since they decline further, this suggests an increase in capital investment, which aligns with the negative contribution of investing cash flows to the cash-return and cash-dispersion covariances reported in Table 9 Panel B. The increase in capital investment appears to contradict the empirical prediction in Bloom (2009), which posits that firms tend to freeze capital investment when uncertainty rises. However, the model in Bloom (2009) does not account for the impact of uncertainty on the price of risk, because productivity-based uncertainty under his study does not predict future equity premia. In contrast, given the focus of price-based uncertainty, this paper shows that heightened uncertainty reduces the perceived riskiness of future profits, thereby increasing their present value and encouraging firms to invest more. The evidence in Table 9 Panel B supports this theoretical prediction.

Overall, the impulse response analysis confirms that uncertainty-induced aggregate movements generate a positive correlation between return dispersion and cash savings, and a negative correlation between cash savings and future returns. It also reveals that these relationships are driven by a negligible contribution from operating cash flows, a negative contribution from investing cash flows, and a positive contribution from financing cash flows. These results are consistent with the conditional moments reported in Table 9 Panel B.

3.3.4 Inspecting the Mechanism

This section examines the structural features of the model that enable it to generate the negative correlation between aggregate cash savings and future excess market returns. Table 10 compares key moments across alternative model specifications and the baseline calibration. These alternatives include: (1) the case with various investment and financing frictions, such as $\theta = 0$, $\theta_-/\theta_+ = 10$, $\lambda_1 = 0$, and $\lambda_2 = 0$; (2) the case without time-varying risk prices, $\gamma_z = 0$; and (3) the case without exogenous firm exits, $\pi = 1$. I discuss each specification in turn below.

Investment and financing frictions. I sequentially shut down the capital adjustment costs and the fixed and quadratic financing costs to examine how these frictions affect the negative cash-return relationship. I also assess the role of capital adjustment asymmetry by setting the downward adjustment cost to $\theta_- = 3.6$, ten times the upward adjustment cost θ_+. Table 10 shows that the unconditional and conditional correlations are nearly identical to the benchmark in all cases, except for the case with zero fixed financing cost (i.e. $\lambda_1 = 0$). In this case, the correlations involving aggregate cash savings fall to zero, while the correlation between return dispersion and future market returns remains unchanged. Moreover, the average cash-to-asset ratio and average aggregate cash savings both drop to near zero.

These results yield three main takeaways. First, they underscore the importance of fixed financing costs in sustaining meaningful cash levels. Not surprisingly, when the cash level drops close to zero at $\lambda_1 = 0$, aggregate cash savings exhibit negligible correlations with return dispersion and future excess market returns. This finding is consistent with Eisfeldt and Muir (2016), who also emphasize the role of fixed costs in explaining the extensive margin of external finance over the business cycle. Second, the dynamics of aggregate cash holdings do not critically depend on capital adjustment costs. This is evident from the correlation results when $\theta = 0$ or $\theta_-/\theta_+ = 10$. As long as capital is being adjusted, regardless of the adjustment speed, firms change their cash holdings in similar ways in order to avoid incurring future fixed financing costs. Third, fixed financing costs can substitute for investment frictions in generating risk. Even in the absence of capital adjustment costs ($\theta = 0$), the presence of a fixed financing cost alone is sufficient to make capital adjustment costly, thereby inducing a positive covariance between returns and productivity shocks, as reflected in Equation 2.

Time-varying price of risk. A model with a constant price of risk cannot replicate a sizable negative correlation between aggregate cash savings and future excess returns. In Table 10, the unconditional cash-return correlation is insignificant at -0.17, and the conditional correlation further declines to -0.08. Importantly, the time-varying price of risk affects the cash-return correlations mostly through the link between uncertainty and future market returns. The moments related to aggregate savings and investment rates under Column $\gamma_z = 0$ show minimal deviations from the benchmark, and the correlation between cash savings and return dispersion remains significantly positive. However, the correlation between return dispersion and future market returns become insignificant.

These results demonstrate the quantitative importance of the channels through which uncertainty impacts corporate saving decisions and future equity premia. Regarding cash savings, the persistent positive correlation between cash changes and return dispersion reflects the option-value channel of cash holdings described in Equation 1: even in the absence of a time-varying price of risk, higher future productivity variance raises investment likelihood, thereby increasing firms' incentive to hold cash. For future returns, although uncertainty also affects firms' cash-to-capital ratios and thus alters the covariance between their equity returns and aggregate productivity shocks in Equation 2, the primary mechanism operates through the effect of uncertainty on the price of risk. When this channel is shut down, the correlation between return dispersion and future returns becomes insignificant. Overall, for cash changes to contain meaningful predictive information about future equity premia, a time-varying price of risk is a necessary condition. This finding is consistent with Belo et al. (2023), who also demonstrate that the time-varying price of risk is a key driver of the return predictive power of aggregate labor hiring rates.

Firm exit. The continuation probability also plays an important role in shaping the relationship between aggregate cash savings and future returns. This dimension is particularly intriguing, as it has received little attention in the existing production-based asset pricing literature. As shown in Table 10 Column $\pi = 1$, the volatility of aggregate cash savings far exceeds its mean, reflecting substantial variability in this variable. At the same time, the correlations between cash changes and either future excess returns or return dispersion become statistically insignificant at the 10% level, whereas the correlations between return dispersion and future returns remain significantly negative.

To understand these changes in moments, I examine the impulse responses in Figure 3. Figures 3A and 3B show that the responses of return dispersion and market returns are nearly identical to those in the benchmark case, indicating a robust positive correlation between return dispersion and future market returns. Interestingly, changes in asset composition have little effect on these impulse responses, underscoring the central role of time-varying risk prices in Equation 2 in driving equity premium responses.

When $\pi = 1$, firms have stronger incentives to hold capital, as reflected in the lower cash-to-asset ratio reported in Table 10. As shown in Figure 3D, following an uncertainty shock, firms initially over-invest, and their investment levels take an extended period to revert to normal. This behavior arises because liquidation losses become less of a concern to them. Given their low baseline cash holdings, firms rely heavily on external financing, leading to a surge in cash changes, up to 25 times their pre-shock level. This aggressive response is driven by at least three forces. First, heightened demand for investment funds increases the value of cash balances $\varphi_{e,t+1}$ in Equation 1. Second, firms are less concerned about cash becoming useless in future periods. According to Equation 1, a higher π amplifies firms' responsiveness to uncertainty shocks, increasing the incentive for precautionary saving. Third, the fixed costs of external financing dominates the quadratic costs, encouraging large financing flows. After the initial shock, firms continue to draw down cash to fund investment until quarter 3, eventually pushing cash changes below pre-shock levels. As a result, the dynamics of cash changes become decoupled from those of return dispersion and uncertainty shocks, thereby weakening their correlation with future excess market returns.

In conclusion, fixed financing costs, a time-varying price of risk, and firm exit are essential ingredients for the model to replicate the return predictive power of aggregate corporate savings. Intuitively, fixed financing costs incentivize firms to hold sufficiently high levels of cash, preventing aggregate savings from becoming negligible. The time-varying price of risk is the key mechanism linking uncertainty to future excess returns. Finally, firm exit tempers firms' responses to uncertainty shocks, thereby smoothing the path of cash adjustments.

4 Implications for Aggregate Accruals

This section investigates whether the return predictive power of aggregate accruals diminishes after controlling for aggregate cash savings, given that cash changes and accruals are mechanically correlated by construction.

The positive correlation between aggregate accruals and future market returns, as identified by Hirshleifer et al. (2009), has garnered considerable attention in the literature. This finding is puzzling, as it contrasts with the well-established negative relation between accruals and future returns in the cross-section (Sloan, 1996). Previous studies have attributed this aggregate-level anomaly to conditional risk premia, systematic earnings management, or merger and acquisition activity (e.g., Guo and Jiang, 2011; Kang et al., 2010; Heater et al., 2021). However, the positive time-series correlation between accruals and returns is not consistently observed at the sector or portfolio levels. Notably, it appears to be concentrated among very large firms (Kang et al., 2010). The earnings management explanation is not sufficient, as there is limited evidence that large firms engage in more earnings manipulation than small or mid-sized firms.[15] In addition, the explanation based on conditional risk premia does not clarify why the accruals of small firms do not exhibit a similar return pattern as large firms, nor does it provide a theoretical basis for why aggregate accruals should positively predict equity premia.

Existing studies on aggregate accruals typically calculate accruals from balance sheet data, defining them as net working capital investment minus depreciation and amortization. This construction implies a natural association with cash changes and capital investment. On one hand, net working capital investment is likely to covary with cash holdings, as firms often liquidate working capital to bolster cash reserves during adverse conditions. For example, Kim (2021) documents that firms reduced inventories to increase cash in response to negative credit supply shocks during the 2008 financial crisis. Firms may also become reluctant to extend credit lines to customers when facing adverse shocks. On the other hand, capital investment strongly correlates with depreciation and amortization, and existing studies document a negative association between capital investment and future risk premia (e.g., Arif and Lee, 2014). Therefore, the documented positive relationship between aggregate accruals and future excess market returns may be spurious, arising from the combined negative correlations between returns and both cash savings and capital investment.

To test this hypothesis, I first replicate the predictive results on aggregate accruals from prior studies. I then decompose aggregate accruals into aggregate net working capital investment and aggregate depreciation and amortization. By conducting horse race regressions

[15]For instance, there is a lack of support in both CEO contracts and turnovers for the notion that CEOs in large firms have higher incentives to manage earnings. According to Murphy (1999), in large-sized firms, the change in CEO wealth is less sensitive to changes in shareholder value than in small firms. Similarly, Jenter and Lewellen (2021) find evidence that larger firms experience less performance-induced turnover and a higher prevalence of normal retirement.

among the components of aggregate accruals, aggregate cash savings, and aggregate capital investment, I assess their respective contributions to the return predictability of aggregate accruals. Table 11 Panel A Column 2 suggests that the predictive power of aggregate accruals stems from both aggregate net working capital investment and aggregate depreciation and amortization. However, once aggregate cash savings are included in Column 3, the coefficient on net working capital investment becomes insignificant and even turns negative. A similar pattern emerges in the results in Column 4 about aggregate depreciation and amortization. Columns 5 and 6 reveal that the predictive power of aggregate accruals is entirely subsumed by the inclusion of both aggregate cash savings and aggregate capital investment, and not when capital investment is considered alone. In Column 6, both aggregate cash savings and capital investment retain statistically significant coefficients, underscoring their independent contributions to explaining future returns. This independence suggest that aggregate cash savings and capital investment seem to capture two distinctive dimensions of macroeconomic conditions, uncertainty levels and productivity levels, respectively. Aggregate investment, as documented in Arif and Lee (2014), exhibits strong cyclical patterns and its ability to predict future market returns is driven by its predictive power on future economic growth. On the other hand, this paper shows that cash savings exhibit a strong correlation with economic uncertainty.

In addition, I investigate the cross-sectional heterogeneity in the return predictive power of aggregate accruals by dividing the sample into R&D-intensive and non-R&D-intensive subsamples and repeating the tests in Panel A. R&D-intensive firms are defined as those belonging to the SIC three-digit industry quintile with the highest R&D intensity, as discussed above. The results in Panel B of Table 11 indicate that, consistent with the findings for aggregate cash savings, aggregate accruals exhibit stronger predictive power for future returns in the R&D-intensive subsample than in the non-R&D subsample. However, in Column 5 of Panel B, the return predictive power of aggregate accruals disappears for the R&D-intensive subsample after controlling for aggregate cash savings and capital investment.

Table 12 reports the results of return prediction horse-race regressions across size quintiles. Consistent with Kang et al. (2010), aggregate accruals positively predict future equity premia only among the largest firms. Across all portfolio-level tests, the predictive power of accruals diminishes once cash savings and capital investment are included as controls. In contrast, the predictive power of cash savings remains significant across all size groups. Further analysis in the last panel of the table reveals that the ability of aggregate accruals to predict returns in the largest firms stems from the particularly strong negative correlation between net working capital investment and cash savings in this group. This finding underscores the importance of recognizing the heterogeneity in the working capital adjustment behavior of the very large firms.

In conclusion, these results suggest that the return predictive power of aggregate accruals lacks robustness, and even more intriguing is to understand the predictive power of aggregate savings. The evidence on aggregate accruals further supports the independent roles of aggregate cash savings and capital investment in forecasting future returns. This motivates the joint consideration of both variables in the out-of-sample tests. As reported in the online appendix, the return predictability of cash savings persists across a battery of out-of-sample tests in Goyal et al. (2024). A market timing strategy based on aggregate cash savings and capital investment achieves excess returns of 2.55% relative to a buy-and-hold strategy.

5 Concluding Remarks

Using a bottom-up measure constructed from firm-level financial disclosures, I document a robust negative association between aggregate cash savings and future excess market returns in the U.S. and across international markets. Decomposition analyses reveal that this predictive power is largely attributable to firms' business-related, risk-free investment activities rather than to risky financial asset investments. I also provide evidence suggesting the role for economic uncertainty in explaining the cash-return relationship. To interpret these findings, I develop and calibrate a heterogeneous firm model, which replicates a number of empirical moments and captures the joint dynamics of cash savings, uncertainty, and future equity premia. Economic uncertainty increases cash accumulation by both enhancing the option value of cash and lowering the perceived risk of future financing cost savings, while simultaneously depressing the price of risk and thus expected returns. Taken together, these effects generate a negative correlation between cash changes and future market premia.

The market return predictive ability of aggregate cash savings provides an alternative explanation for the aggregate accruals puzzle. After controlling for aggregate cash savings and aggregate capital investment, the return predictive ability of aggregate accruals drops to nearly zero. I find that net working capital investment is negatively associated with cash changes, especially among large firms. This finding raises an intriguing research question: why do large firms exhibit a greater responsiveness of net working capital investment to liquidity needs? This heterogeneity is likely attributable to the enhanced market power of large firms, which provides them with more flexibility in adjusting the credit they extend over the supply chain when encountering headwinds.

A Appendix

A.1 Variable Description

Table A.1: Definition of Main Variables
This table presents the calculation method of the main variables used in empirical analysis.

Items	Description
$ExMk(Sm)Ret_t$	Excess market returns, compounded CRSP monthly stock return from May of year t to April of year $t+1$ minus the one-year yield to maturity rate of US treasuries bills at the end of April in year t. $ExSmRet_t$ is calculated as the equal-weighted average of sample firm stock returns from May of year t to April of year $t+1$ minus the one-year treasury yield.
$ChgCash_t$	Aggregate cash savings, the cross-sectional weighted average of cash changes (item CHE) scaled by total assets at the beginning of a year. In return forecasting tests, I aggregate cash savings using cap weights at the end of a year to match the weight choice of future market returns. In the tests about aggregate cash savings determinants, I use cap weights at the beginning of a calendar year to avoid drivers' potential effects on market prices. I trim the top and the bottom 0.5% observations in each year.
$Accruals_t$	Aggregate accruals, the cross-sectional weighted average of accruals scaled by total assets at the beginning of a year. I use the market cap at the end of year t as weights to compute the average. Accruals are computed as net working capital investment minus depreciation and amortization. Net working capital investment is the change in non-cash current assets less the change in current liabilities excluding the change in short-term debt and the change in taxes payable. I trim the top and the bottom 0.5% observations in each year.
$NWCInvt_t$	Aggregate net working capital investment, the cross-sectional weighted average of net working capital investment scaled by total assets at the beginning of a year. The market cap at the end of year t is used as weights to compute the average.
$D\&A_t$	Aggregate D&A, the cross-sectional average of depreciation and amortization scaled by total assets at the beginning of a year. I choose the market cap at the end of year t as weights.
$CapInvt_t$	Aggregate capital investment, the cross-sectional average of the change in net PP&E plus depreciation and amortization scaled by total assets at the beginning of a year. I choose the market cap at the end of year t as weights to compute the average.
$Default_t$	Default premium, the difference between the Moody's seasoned Baa corporate bond yield and Aaa yield as of the end of April in year $t+1$.
$Term_t$	Term premium, the difference between ten- and one-year Treasury yield to maturity as of the end of April in year $t+1$.
$EQIS_t$	The equity share in total equity and debt issuance in t as in Baker and Wurgler (2000).
E/P_t	Aggregate earnings-to-price ratio, weighted by market cap at the end of year t. The firm-level earnings-to-price ratio is computed as operating income after depreciation scaled by market cap at year end.
B/M_t	Aggregate book-to-market ratio, weighted by market cap at the end of year t. Firm-level book value is computed following the method in Davis et al. (2000).
D/P_t	Market dividend-to-price ratio, equals to total dividend accrued to the CRSP value-weighted index from May in year t to April in year $t+1$ divided by the index level at the end of April in year $t+1$.
$RetDisp_t$	The cross-sectional size-weighted standard deviation of firm-level stock returns in year t as in Angelidis et al. (2015). I trim the top and the bottom 0.5% observations in each year.

A.2 Numerics

To solve for the competitive equilibrium along the balanced growth path, I define the detrended variables $\hat{V}_{it} = V_{it}/Z_{i,t-1}$, $\hat{J}_{it} = J_{it}/Z_{i,t-1}$, $\hat{K}_{it} = K_{it}/Z_{i,t-1}$, $\hat{L}_{it} = L_{it}/Z_{i,t-1}$, $\hat{D}_{it} = D_{it}/Z_{i,t-1}$, $\hat{E}_{it} = E_{it}/Z_{i,t-1}$, $\hat{Y}_{it} = Y_{it}/Z_{i,t-1}$, $\hat{I}_{it} = I_{it}/Z_{i,t-1}$. The stationary problem of incumbents with state variables $(\hat{K}_{it}, \hat{L}_{it}, Z_{it}/Z_{i,t-1}, \sigma_{zt}, x_t)$ can be written as:

$$\hat{V}_{it} = \max_{\hat{K}_{i,t+1}, \hat{L}_{i,t+1}} \hat{D}_{it} + \pi \frac{Z_{it}}{Z_{i,t-1}} \mathbb{E}_t[M_{t+1}\hat{V}_{i,t+1}] + (1-\pi)\frac{Z_{it}}{Z_{i,t-1}} \mathbb{E}_t\left[M_{t+1}\left(\hat{L}_{i,t+1} + \phi \hat{J}_{i,t+1}\right)\right]$$

s.t.

$$\hat{D}_{it} = \hat{E}_{it} - \left(\lambda_1 + \frac{1}{2}\lambda_2 \hat{E}_{it}^2\right)\mathbb{I}_{\hat{E}_{it}<0}$$

$$\hat{E}_{it} = \hat{Y}_{it} - \hat{I}_{it} - \frac{1}{2}\theta\left(\frac{\hat{I}_{it}}{\hat{K}_{it}}\right)^2 \hat{K}_{it} + \hat{L}_{it} - \frac{\hat{L}_{i,t+1}}{1+r_s}\frac{Z_{it}}{Z_{i,t-1}}$$

$$\hat{Y}_{it} = \left(\frac{Z_{it}}{Z_{i,t-1}}\right)^{1-\alpha} e^{(1-\alpha)x_t} \hat{K}_{it}^{\alpha}$$

$$\hat{K}_{i,t+1}\frac{Z_{it}}{Z_{i,t-1}} = (1-\delta)\hat{K}_{it} + \hat{I}_{it},$$

where the detrended asset value is given by

$$\hat{J}_{it} = \hat{Y}_{it} + \mathbb{E}_t\left[M_{t+1}\hat{J}_{i,t+1}\right]\frac{Z_{it}}{Z_{i,t-1}}.$$

The stock return of incumbents is given as follows:

$$R_{i,t+1} = \frac{\pi \hat{V}_{i,t+1} + (1-\pi)\left(\hat{L}_{i,t+1} + \phi \hat{J}_{i,t+1}\right)}{\hat{V}_{it} - \hat{D}_{it}}\frac{Z_{it}}{Z_{i,t-1}}$$

Accordingly, the stationary problem of entrants with state variables $(Z_{it}/Z_{i,t-1}, \sigma_{zt}, x_t)$

can be written as:

$$\hat{V}_{it}^{E} = \max_{\hat{K}_{i,t+1},\hat{L}_{i,t+1}} \frac{Z_{it}}{Z_{i,t-1}} \left\{ -\hat{K}_{i,t+1} - \frac{\hat{L}_{i,t+1}}{1+r_s} + \mathbb{E}_t \left[M_{t+1} \left(\pi \hat{V}_{i,t+1} + (1-\pi)(\hat{L}_{i,t+1} + \phi \hat{J}_{i,t+1}) \right) \right] \right\}.$$

I use the value function iteration method to solve the firm's maximization problems. I specify a grid with 50 points for capital and cash separately, and construct the grids recursively using $\hat{K}_i = \hat{K}_{i-1} + c_1 \exp(c_2(i-2))$ and $\hat{L}_i = \hat{L}_{i-1} + c_3 \exp(c_4(i-2))$, where $i = 1, 2..., 50$. The stationary process of aggregate productivity X_t is first converted into its log forms, $x_{t+1} = (1-\rho_x)\bar{x} + \rho_x x_t - \sigma_x^2/2 + \sigma_x \varepsilon_{x,t+1}$, and discretized using Rouwenhorst (1995) method. Once the discrete space is available, the value functions for incumbents and entrants are evaluated on a $(\hat{K}_t, \hat{L}_t)$ grid for each exogenous state. Then I adopt a simple discrete global search routine in maximizing the value function. During the simulation, the detrended variables are scaled by $Z_{i,t-1}$ to reflect their actual levels.

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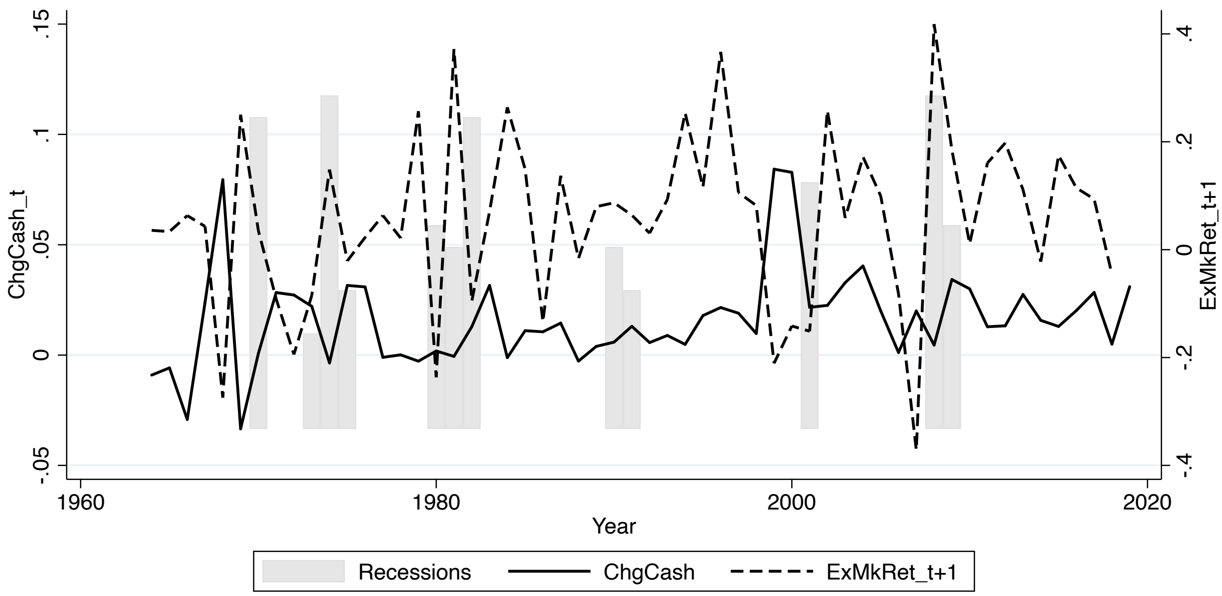
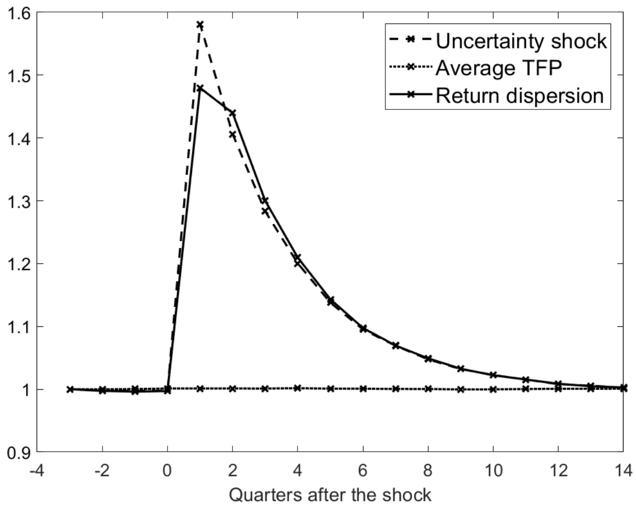
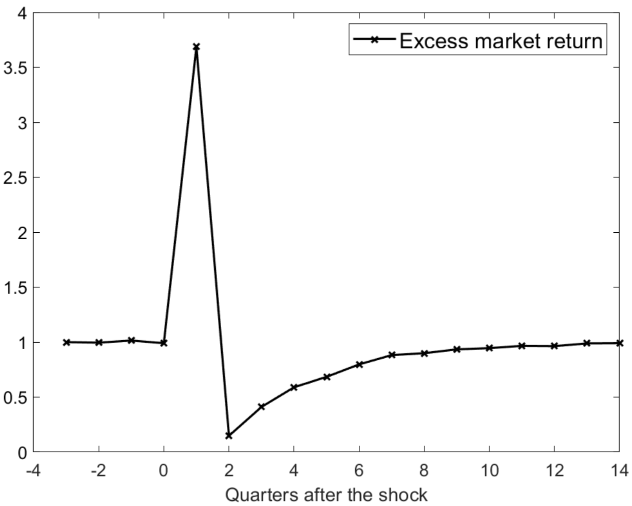


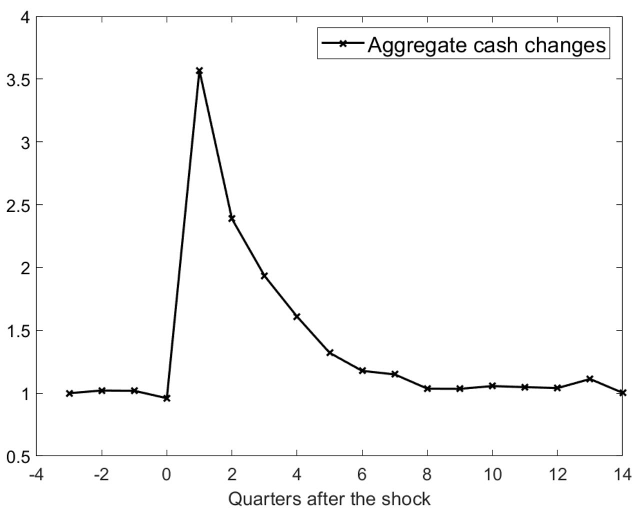
Figure 1: Aggregate Cash Savings and Future Excess Market Returns
This figure depicts the time series of aggregate cash savings and future excess market returns from 1964 to 2019. Cash savings in this context include cash, cash equivalents and short-term investments. The variable $ExMkRet_{t+1}$ represents the CRSP value-weighted excess market returns over the period from May of year $t+1$ to April of year $t+2$. The shaded area indicates the number of months in each year that are identified as NBER recessions. The market returns and aggregate cash savings are not detrended. Corr$(ChgCash_t, ExMkRet_{t+1}) = -0.39$.



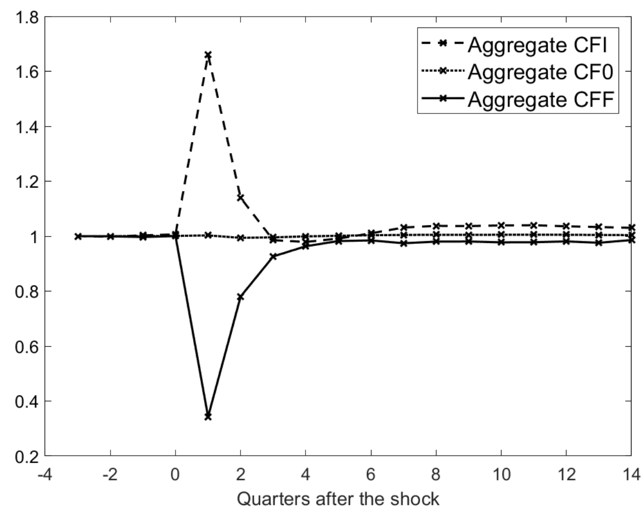
(a) Aggregate shocks and return dispersion



(b) Excess stock market returns

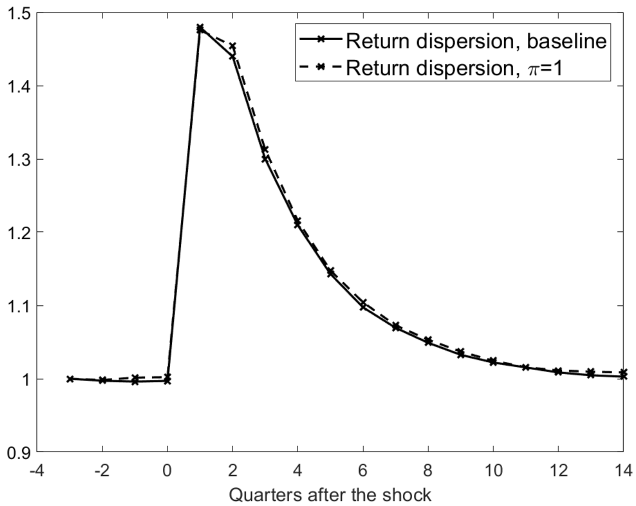


(c) Aggregate cash changes

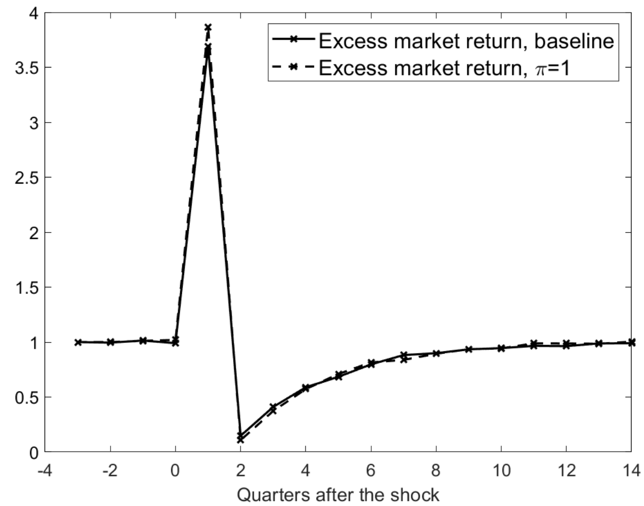


(d) Operating, investing and financing cash flows

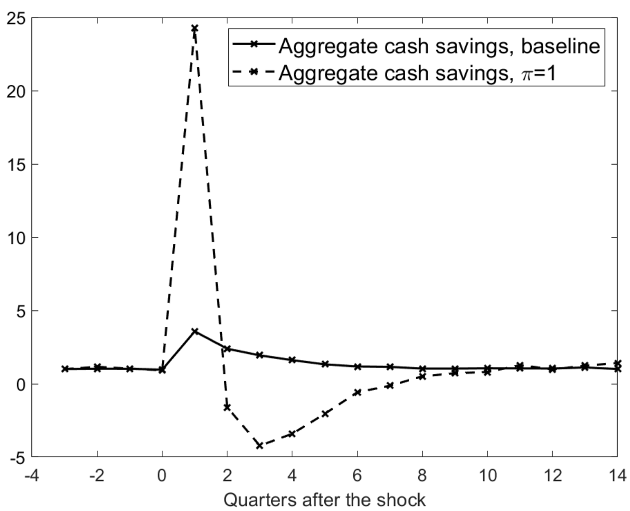
Figure 2: Impulse Response Simulations
I simulate an economy consisting of 4,000 firms over 18 quarters (54 months), repeating the simulation 25,000 times. The plotted variables represent averages across these simulated panels, normalized by their respective steady-state values. In each simulation, the economy is subjected to an uncertainty shock, $\sigma_{zt} = \sigma_H$, at the start of quarter 1, while all other shocks are randomly drawn.



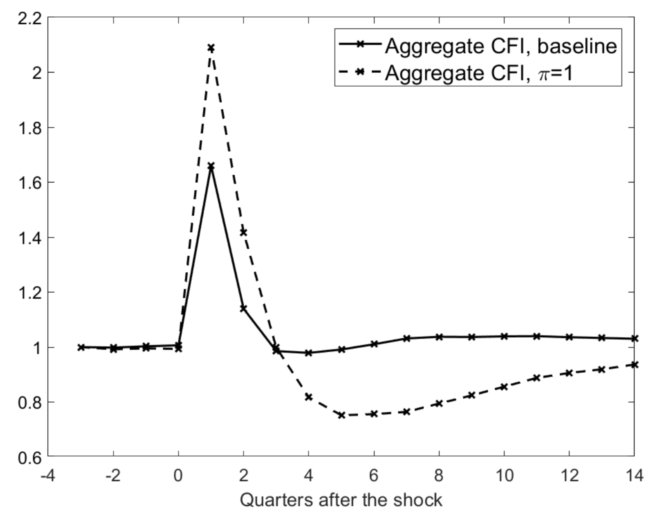
(a) Return dispersion



(b) Excess stock market returns



(c) Aggregate cash changes



(d) Aggregate investing cash flows

Figure 3: Comparison between the Baseline Model and the Alternative with $\pi = 1$
I compare the impulse responses of the baseline model with those of an alternative specification in which $\pi = 1$. For each model, I simulate an economy consisting of 4,000 firms over 18 quarters (54 months), repeating the simulation 25,000 times. The plotted variables represent averages across these simulated panels, normalized by their respective steady-state values. In each simulation, the economy is subjected to an uncertainty shock, $\sigma_{zt} = \sigma_H$, at the start of quarter 1, while all other shocks are randomly drawn.

Table 1: Summary Statistics
The sample period is from 1964 to 2019. The sample includes non-financial firms with fiscal year-ends in December and have common equity issues listed on NYSE, AMEX, or NASDAQ. Below report the summary statistics of aggregate-level variables.

	count	mean	sd	p5	p25	p50	p75	p95
$ExMkRet$	55	0.057	0.161	-0.237	-0.022	0.064	0.149	0.367
$ExSmRet$	55	0.114	0.236	-0.213	-0.045	0.104	0.253	0.493
$ChgCash$	56	0.016	0.022	-0.009	0.003	0.013	0.027	0.079
$ChgCashEq$	56	0.016	0.018	-0.009	0.006	0.014	0.026	0.047
$Accruals$	56	-0.048	0.014	-0.069	-0.052	-0.047	-0.043	-0.031
$NWCInvt$	56	0.011	0.014	-0.006	0.001	0.007	0.016	0.038
$D\&A$	56	0.059	0.015	0.045	0.048	0.058	0.061	0.101
$CapInvt$	56	0.109	0.035	0.067	0.084	0.102	0.126	0.191
$RetDisp$	56	0.286	0.081	0.199	0.238	0.261	0.327	0.459
$Default$	56	0.010	0.005	0.006	0.007	0.009	0.012	0.021
$Term$	56	0.010	0.011	-0.007	0.001	0.009	0.017	0.029
$EQIS$	56	0.166	0.086	0.075	0.106	0.142	0.213	0.362
E/P	56	0.139	0.071	0.062	0.090	0.115	0.171	0.307
D/P	56	0.028	0.011	0.013	0.020	0.027	0.035	0.049
B/M	56	0.609	0.274	0.303	0.404	0.522	0.773	1.163

Table 2: Aggregate Cash Savings and Future Excess Market Returns

In Panel A, I present the results about the return predictive power of cash savings at the aggregate level. $ExMkRet$ represents the CRSP excess market returns, and the corresponding $ChgCash_{t-1}$ values are calculated using the capitalization weights at year $t-1$ end. On the other hand, $ExSmRet$ represents the equal-weighted average of sample firm excess stock returns, with the corresponding $ChgCash_{t-1}$ values computed using equal weights. In Panel B Columns 1-5, I divide firms in each year into size quintiles based on firms' market capitalization in the beginning of a year. Cash savings and stock returns are aggregated within each quintiles using the capitalization weights at year $t-1$ end. Columns 1-5 report results about size quantiles from the smallest to the largest. In Column 6, I regress future excess returns on cash savings for each firm with no fewer than 10 observations and report the cross-sectional averages of the estimated coefficients and adjusted R^2 values. t-statistics are reported in parenthesis and except for Panel B Column 6, are corrected for autocorrelation using Newey-West method lagging three periods . *, **, *** denote statistical significance at 10%, 5%, 1% levels respectively.

(a) The return predictive power at the aggregate level

	(1) $ExMkRet$	(2) $ExMkRet$	(3) $ExMkRet$	(4) $ExSmRet$	(5) $ExSmRet$	(6) $ExSmRet$
$ChgCash_{t-1}$	-2.910***	-2.948***	-2.734***	-4.394**	-3.839***	-3.285**
	(-4.51)	(-5.81)	(-2.96)	(-2.66)	(-2.92)	(-2.58)
$Default_{t-1}$		5.299	5.840		9.711	13.585**
		(1.33)	(1.52)		(1.66)	(2.38)
$Term_{t-1}$		3.075***	3.919***		4.150**	6.345***
		(2.91)	(2.84)		(2.38)	(3.87)
$EQIS_{t-1}$		-0.091	-0.038		-0.055	0.220
		(-0.38)	(-0.11)		(-0.15)	(0.46)
E/P_{t-1}			0.951			2.945***
			(0.93)			(3.36)
D/P_{t-1}			1.067			1.944
			(0.17)			(0.36)
B/M_{t-1}			-0.285			-0.915***
			(-1.17)			(-3.68)
Constant	0.103***	0.033	0.018	0.187***	0.044	0.021
	(5.11)	(0.56)	(0.17)	(5.18)	(0.59)	(0.19)
Adj R squared	0.139	0.172	0.134	0.097	0.133	0.144
Obs	55	55	55	55	55	55

(b) The return predictive power at the size portfolio and individual firm level

	(1) $ExRet_1$	(2) $ExRet_2$	(3) $ExRet_3$	(4) $ExRet_4$	(5) $ExRet_5$	(6) $ExRetF$
$ChgCash_{t-1}$	-1.163*	-1.289***	-1.432***	-1.081***	-2.533***	-0.491***
	(-1.86)	(-3.59)	(-2.75)	(-3.74)	(-4.21)	(-4.33)
Constant	0.156***	0.160***	0.141***	0.094***	0.085***	0.149***
	(3.25)	(5.16)	(4.51)	(5.08)	(4.65)	(36.69)
Adj R squared	0.020	0.068	0.059	0.067	0.133	0.001
Obs	55	55	55	55	55	2142

Table 3: International Evidence about Aggregate Cash Savings and Future Excess Market Returns
This table presents the in-sample univariate regression results about the cash-return relation for each market. Aggregate excess stock returns are calculated as the average of firm excess stock returns from May of year t to April of year $t+1$ weighted by the market capitalization at year t end. Aggregate cash savings are the average of year t scaled cash changes weighted by the market capitalization at year t end. Estimated coefficients of aggregate cash savings are reported under the coefficient column. t-statistics are corrected for autocorrelation using Newey-West method lagging three periods. I also calculate the cross-market average of estimated coefficients and report the corresponding t-statistics. Pooled estimate is computed from a panel regression with market fixed effects using market-year panel data, and its t-statistic clustered by year and market is reported in parenthesis. *, **, *** denote statistical significance at 10%, 5%, 1% levels respectively.

Market	Starting Year	Length	Avg Firm/Year	Coefficient	t-stat.	Adjusted R^2
Australia	2001	20	127	1.76	1.20	-0.01
Belgium	2000	21	77	-2.29*	-1.92	-0.01
Brazil	2001	20	157	3.91	0.46	-0.05
China	1999	22	1836	-6.68**	-2.23	0.21
Denmark	1997	24	62	-5.39***	-3.50	0.23
Finland	1998	23	101	-0.87	-0.47	-0.04
France	1990	31	332	-3.19*	-1.77	0.03
Germany	1990	31	349	-1.69***	-5.10	0.10
Hong Kong	1997	24	412	-1.74***	-2.93	0.08
Indonesia	1997	24	251	-2.41	-0.70	-0.03
Italy	1997	24	177	-1.72***	-5.38	0.04
Japan	1997	24	221	-0.58	-0.36	-0.04
Malaysia	1995	26	354	-3.77	-1.01	0.02
Netherlands	1994	27	92	-2.87**	-2.32	0.05
Norway	1997	24	122	-0.62	-0.64	-0.03
Philippines	1998	23	111	-0.13	-0.13	-0.05
Poland	2002	19	327	-4.26***	-5.06	0.27
Singapore	1995	26	218	-1.29**	-1.91	0.01
South Korea	1995	26	678	2.87	0.56	-0.03
Spain	1995	26	93	-5.33	-1.63	0.04
Sweden	1997	24	302	-7.57	-1.40	0.18
Switzerland	1998	23	130	-3.48***	-7.91	0.37
Taiwan	1998	23	1133	-4.97**	-2.59	0.18
Thailand	1995	26	314	-2.63	-0.50	-0.02
United Kingdom	1990	31	422	-0.57	-0.89	-0.03
Cross-sectional average				-2.22***	-4.04	
Pooled estimate				-1.89***	-4.05	

Table 4: Comparison with Cross-Sectional Predictors

I independently assess the return predictive capabilities of aggregate cross-sectional predictors in Columns 1-3 and compare their forecasting performance with aggregate corporate savings in Columns 4-6. $Cash_{t-1}/Asset_{t-1}$ is the cash level in Palazzo (2012), $(Asset_{t-1} - Asset_{t-2})/Asset_{t-2}$ is the investment-to-asset ratio in Hou et al. (2015), and $Cash_{t-1}/Asset_{t-1} - Cash_{t-2}/Asset_{t-2}$ is the cash change ratio in Sodjahin (2013). The calculation of aggregate cross-sectional predictors utilizes the same capitalization weights as aggregate corporate savings $ChgCash_{t-1}$. t-statistics are reported in parenthesis and are corrected for auto-correlation using Newey-West method lagging three periods. *, **, *** denote statistical significance at 10%, 5%, 1% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$ExMkRet$	$ExMkRet$	$ExMkRet$	$ExMkRet$	$ExMkRet$	$ExMkRet$
$ChgCash_{t-1}$				-2.716***	-2.324**	-3.724***
				(-4.11)	(-2.18)	(-5.02)
$Cash_{t-1}/Asset_{t-1}$	-1.019*			-0.421		
	(-1.77)			(-0.76)		
$Asset_{t-1}/Asset_{t-2} - 1$		-0.824***			-0.397	
		(-2.88)			(-0.90)	
$\Delta(Cash_{t-1}/Asset_{t-1})$			-2.457*			1.489
			(-1.73)			(0.90)
Constant	0.170***	0.171***	0.048**	0.147**	0.149***	0.122***
	(2.77)	(4.05)	(2.26)	(2.38)	(2.86)	(4.33)
Adj R squared	0.022	0.083	0.039	0.128	0.140	0.131
Obs	55	55	55	55	55	55

Table 5: Decomposing Aggregate Corporate Savings

The change in cash savings ($ChgCash_{t-1}$) is decomposed into seven components: operating cash flows ($OANCF_{t-1}$), operating asset investing cash flows ($-AQC_{t-1} - CAPX_{t-1} + SPPE_{t-1}$), financial asset investing cash flows ($INVCF_{t-1} + AQC_{t-1} + CAPX_{t-1} - SPPE_{t-1}$), financing cash flows ($FINCF_{t-1}$), exchange rates ($EXRE_{t-1}$), short-term investments ($\Delta INVST_{t-1}$), and the opposite impact of restricted cash investment ($-\Delta RSTCHE_{t-1}$). $-\Delta RSTCHE_{t-1}$ is computed by substracting the other six components from ΔCHE_{t-1}. Each component is scaled by total assets at the beginning of a year. The covariances between cash savings and return dispersion or future market excess returns are decomposed into the covariances with respect to these seven components. Beyond the sample used in the main analysis, this table further restricts the sample to observations with non-missing data for each component. This restriction limits the analysis to the sample period from 1988 to 2020, with an average of 1,153 firms per year. Reported covariances in this table have been scaled by 1,000. t-statistics are reported in parentheses.

	$\Gamma = ExMkRet_t$	% of Total	$\Gamma = RetDisp_{t-1}$	% of Total
Corr($ChgCash_{t-1}, \Gamma$)	-0.43		0.58	
	(-2.12)		(3.86)	
Decompose covariances into:				
Operating cash flows	-0.34	17%	0.48	48%
Investing cash flows	1.94	-98%	-1.02	-102%
Operating asset investing	0.94	-48%	-0.71	-70%
Financial asset investing	1.00	-50%	-0.31	-31%
Financing cash flows	-2.58	131%	1.01	100%
Exchange rates	-0.02	1%	0.02	2%
Short-term investment	-0.84	43%	0.49	49%
- Restricted cash investment	-0.12	6%	0.02	2%
Total Cov($ChgCash_{t-1}, \Gamma$)	-1.97	100%	1.00	100%

Table 6: Aggregate Cash Savings, Economic Uncertainty and Future Excess Returns
Panel A Columns 1-5 report the results about size quantiles with the smallest to the largest firm size. Column 6 reports the results using the full sample with capitalization weights. Unlike the aggregation method in return prediction tests, to avoid explanatory variables' potential impacts on year-end capitalization weights, I aggregate cash savings using capitalization weights at the beginning of a year. The control variable $Trend$ is a linear time trend. t-statistics are reported in parenthesis and are corrected for autocorrelation using Newey-West method lagging three periods. Panel B compares the estimated coefficients of $ChgCash_{i,t-1}$ in regressions without and with economic uncertainty measures based on the following specifications:

$$ExRet_{i,t} = \mu_i + \beta_1 ChgCash_{i,t-1} + \beta_2 Trend_{t-1} + \varepsilon_{i,t}$$

$$ExRet_{i,t} = \mu_i + \beta_1 ChgCash_{i,t-1} + \beta_2 Trend_{t-1} + \beta_3 RetDisp_{t-1} + \varepsilon_{i,t}$$

where $ExRet_{i,t}$ and $ChgCash_{i,t-1}$ are portfolio-level aggregate excess returns and cash changes. I sort observations in each year into terciles based on the Fama-French ten industries, market capitalization, book-to-market ratio or investment-to-asset ratio. t-statistics clustered by firm and year are reported in parenthesis in Columns Without and With. Under Column Change, p-values are reported in parenthesis. The p-values are calculated from χ^2 tests with the null hypothesis that the coefficients of $ChgCash_{i,t-1}$ are the same in regressions with and without the uncertainty measure.

(a) The determinants of aggregate corporate savings

	(1) $ChgCash_1$	(2) $ChgCash_2$	(3) $ChgCash_3$	(4) $ChgCash_4$	(5) $ChgCash_5$	(6) $ChgCash$
$RetDisp$	0.062*	0.108**	0.108***	0.137***	0.063**	0.070***
	(1.78)	(2.62)	(3.89)	(3.93)	(2.67)	(3.16)
$Trend$	-0.006	0.025*	0.039***	0.031***	0.015	0.017
	(-0.33)	(1.83)	(3.38)	(2.79)	(1.04)	(1.34)
Adj R squared	0.012	0.099	0.243	0.415	0.060	0.099
Obs	56	56	56	56	56	56

(b) The explanatory power of economic uncertainty measures

	Without	With	Change	Change%
10 Sector Portfolios	-1.031	-0.792	0.239	23.2%
	(-2.41)	(-1.86)	(0.01)	
10 Size Portfolios	-2.679	-2.459	0.220	8.2%
	(-3.30)	(-2.72)	(0.09)	
10 BM Portfolios	-1.296	-1.094	0.203	15.7%
	(-2.94)	(-2.59)	(0.00)	
10 INV Portfolios	-1.313	-1.032	0.280	21.4%
	(-3.92)	(-3.31)	(0.00)	

Table 7: Heterogeneity in the Forecasting Power of Aggregate Cash Savings
Panel A presents the predictive capability of aggregate cash savings across various groups with differing R&D intensity. Panel A Columns 1-5 report results about R&D intensity groups from the lowest to the highest. SIC three-digit industries are categorized into quintiles based on the average R&D investment as a percentage of total assets since 1964. Panel B presents the results for groups with differing book-to-market ratios. Firms are sorted into quintiles in each year based on the difference between their BM ratios and the corresponding R&D or non-R&D group average BM ratio. Panel B Columns 1-5 report results about groups from the lowest BM ratio to the highest. For companies in each quintile, I aggregate corporate savings and future excess returns within their respective group and perform separate regressions for each group. t-statistics are reported in parenthesis and are corrected for autocorrelation using Newey-West method lagging three periods. *, **, *** denote statistical significance at 10%, 5%, 1% levels respectively.

(a) The return predictive power for R&D portfolios

	(1)	(2)	(3)	(4)	(5)
	$ExRet_1$	$ExRet_2$	$ExRet_3$	$ExRet_4$	$ExRet_5$
$ChgCash_{t-1}$	-3.087	-1.666	-0.868	-1.437	-1.700***
	(-1.45)	(-0.74)	(-0.77)	(-0.77)	(-4.37)
Constant	0.083***	0.070***	0.060***	0.064***	0.105***
	(2.78)	(3.26)	(2.81)	(2.97)	(4.05)
Adj R squared	0.020	-0.004	-0.013	-0.005	0.114
Obs	55	55	55	55	55

(b) The return predictive power for BM portfolios

	(1)	(2)	(3)	(4)	(5)
	$ExRet_1$	$ExRet_2$	$ExRet_3$	$ExRet_4$	$ExRet_5$
$ChgCash_{t-1}$	-2.487***	-1.917***	-1.850	-1.524***	0.289
	(-3.08)	(-2.98)	(-1.33)	(-2.70)	(0.13)
Constant	0.091***	0.102***	0.093***	0.088***	0.088***
	(3.45)	(4.25)	(4.38)	(4.17)	(4.09)
Adj R squared	0.067	0.104	0.025	0.034	-0.019
Obs	55	55	55	55	55

Table 8: Baseline Parameter Values
This table gives the baseline parameter values and provides the description of parameter definitions.

Parameter	Value	Description
Stochastic Discount Factor		
β	0.9985	Time discount factor
γ	14	Relative risk aversion coefficient
γ_z	810	Risk factor loading on economic uncertainty
Firms		
α	0.35	Production function curvature
δ	0.1/12	Depreciation rate
θ	0.36	Convex adjustment cost parameter
λ_1	0.04	External financing fixed cost
λ_2	0.0004	External financing quadratic cost
ϕ	0.85	Recovery rate of liquidated assets
π	0.992	Continuation probability
τ	0.20	Corporate tax rate
Level Shocks		
$\bar{x}$	-5.395	Average level of log aggregate productivity
ρ_x	0.985	Persistence of log aggregate productivity
σ_x	0.055	Level of log aggregate productivity volatility
Uncertainty Shocks		
σ_L	0.066	Level of uncertainty shock in the low state
σ_H/σ_L	2.2	Relative magnitude of uncertainty shocks at high and low states
π^{σ}_{LH}	0.03	Transition probability from the low to the high state
π^{σ}_{HL}	0.92	Transition probability from the high to the low state

Table 9: Calibration and Additional Moments

In Panel A, I report the moments used for parameter calibration, while Panels B and C report untargeted moments. In Panel B, correlation coefficients between $ChgCash_{t-1}$ and $ExMkRet_t$, $ChgCash_{t-1}$ and $RetDisp_{t-1}$, and $RetDisp_{t-1}$ and $ExMkRet_t$ are computed based on the full sample, while the contribution percentages are calculated using the restricted sample described in Table 5. To focus on the impact of uncertainty shocks, I compute the contribution percentages of individual cash flows conditional on aggregate TFP. Aggregate TFP in the data are downloaded from the U.S. Bureau of Labor Statistics. Contribution percentages are normalized to sum up to one. In the simulated sample, cash savings are decomposed following: $L_t/(1+r_s) - L_{t-1} = Y_{t-1} - \Theta_{t-1} - I_{t-1} - E_{t-1}$. Operating cash flows are equal to Y_{t-1}; investing cash flows are equal to $-I_{t-1} - \Theta_{t-1}$; and financing cash flows are equal to $-E_{t-1}$, which denotes equity financing proceeds net of external funding costs. These simulated variables have been scaled by total assets in the beginning of a period. In Panel C, for moments computed using data since 1964, $CFO_{t-1} + CFF_{t-1}$ equals $ChgCash_{t-1} + CapInvt_{t-1}$, and CFI_{t-1} corresponds to $-CapInvt_{t-1}$. For moments based on data since 1988, CFO_{t-1}, CFI_{t-1}, and CFF_{t-1} represent operating cash flows, operating asset investing cash flows, and financing cash flows, respectively. Firms are sorted into quintiles in each year based on the difference between their BM ratios and the corresponding R&D or non-R&D group mean BM ratio. Aggregate cash savings and future excess portfolio returns are computed for each group, and moments are reported for the highest and lowest BM quintiles. I report the average simulated moments and their corresponding average t-statistics (in parentheses) across 500 simulations, each spanning 60 years.

(a) Calibration Moments

Moments	Data	Model
Average annual excess market returns	0.057	0.053
Annual volatility of excess market returns	0.16	0.05
Average annual stock return dispersion	0.29	0.35
Average annual stock return dispersion H/L ratio	1.67	1.74
Average cash/asset ratio	0.15	0.11
Average annual aggregate cash savings	0.016	0.012
Annual volatility of aggregate cash savings	0.022	0.030
Average annual aggregate investment rate	0.109	0.111
Annual volatility of aggregate investment rate	0.035	0.054
Corr($ChgCash_t, ExMkRet_{t+1}$)	-0.39	-0.37

(b) Additional Aggregate Moments

Moments	Data	Model
Unconditional Moments		
Corr($ChgCash_{t-1}, RetDisp_{t-1}$)	0.33	0.30
	(2.56)	(2.50)
Corr($RetDisp_{t-1}, ExMkRet_t$)	-0.25	-0.32
	(-1.77)	(-2.66)
Moments Conditional on Aggregate TFP		
Corr($ChgCash_{t-1}, ExMkRet_t$)	-0.37	-0.33
	(-2.55)	(-2.73)
Corr($ChgCash_{t-1}, RetDisp_{t-1}$)	0.39	0.30
	(3.10)	(2.46)
Corr($RetDisp_{t-1}, ExMkRet_t$)	-0.28	-0.33
	(-1.95)	(-2.74)
% Contribution to Cov($ChgCash_{t-1}, ExMkRet_t$)		
Operating cash flows	15%	-11%
Investing cash flows	-52%	-48%
Financing cash flows	136%	159%
% Contribution to Cov($ChgCash_{t-1}, RetDisp_{t-1}$)		
Operating cash flows	63%	-15%
Investing cash flows	-105%	-141%
Financing cash flows	141%	257%

(c) Additional Cross-Sectional Moments

	Data since 1964			Data since 1988			Model		
	Low	High	High-Low	Low	High	High-Low	Low	High	High-Low
Corr($ChgCash_{t-1}, ExRet_t$)	-0.290	0.017	0.306	-0.310	-0.020	0.291	-0.368	-0.037	0.330
	(-2.03)	(0.12)	(1.61)	(-1.60)	(-0.11)	(1.13)	(-3.11)	(-0.29)	(1.90)
Corr($ChgCash_{t-1}, RetDisp_{t-1}$)	0.255	-0.090	-0.346	0.487	-0.090	-0.577	0.339	-0.291	-0.630
	(1.92)	(-0.65)	(-1.80)	(3.01)	(-0.48)	(-2.33)	(2.87)	(-2.37)	(-3.56)
$CFO_{t-1} + CFF_{t-1}$	0.126	0.075	-0.051	0.136	0.068	-0.068	0.217	-0.051	-0.268
	(27.99)	(18.08)	(-10.86)	(19.99)	(19.33)	(-8.73)	(27.48)	(-3.84)	(-18.38)
CFI_{t-1}	-0.112	-0.072	0.040	-0.111	-0.066	0.045	-0.201	0.048	0.249
	(-24.23)	(-17.63)	(9.57)	(-18.95)	(-31.25)	(7.80)	(-26.71)	(5.54)	(26.41)
$ChgCash_{t-1}$	0.015	0.003	-0.011	0.019	0.000	-0.018	0.020	0.002	-0.018
	(6.85)	(2.32)	(-5.71)	(4.66)	(0.31)	(-4.25)	(8.56)	(0.37)	(-2.28)

Table 10: Alternative Model Specifications

This table presents the quantitative results for alternative model specifications. Parameters are adjusted to the values specified in each column, while all other parameters remain consistent with those used in the baseline simulation. I report the average simulated moments and their corresponding average t-statistics (in parentheses) across 500 simulations, each spanning 60 years.

Moments	Baseline	$\pi = 1$	$\gamma_z = 0$	$\theta = 0$	$\theta_-/\theta_+ = 10$	$\lambda_1 = 0$	$\lambda_2 = 0$
Unconditional Moments							
Average cash/asset ratio	0.11	0.06	0.11	0.16	0.09	0.01	0.11
Average annual aggregate cash savings	0.012	0.001	0.010	0.019	0.015	0.000	0.012
Annual volatility of aggregate cash savings	0.030	0.023	0.040	0.062	0.021	0.000	0.032
Average annual aggregate investment rate	0.111	0.086	0.107	0.099	0.107	0.118	0.111
Annual volatility of aggregate investment rate	0.054	0.082	0.044	0.072	0.039	0.079	0.055
Corr($ChgCash_{t-1}, ExMkRet_t$)	-0.37	-0.15	-0.17	-0.34	-0.39	0.06	-0.36
	(-3.07)	(-1.18)	(-1.35)	(-2.81)	(-3.29)	(0.45)	(-3.02)
Corr($ChgCash_{t-1}, RetDisp_{t-1}$)	0.30	-0.01	0.22	0.39	0.20	-0.01	0.33
	(2.50)	(-0.11)	(1.77)	(3.26)	(1.64)	(-0.11)	(2.75)
Corr($RetDisp_{t-1}, ExMkRet_t$)	-0.32	-0.27	0.02	-0.32	-0.31	-0.33	-0.31
	(-2.66)	(-2.17)	(0.15)	(-2.68)	(-2.53)	(-2.70)	(-2.58)
Moments Conditional on Aggregate TFP							
Corr($ChgCash_{t-1}, ExMkRet_t$)	-0.33	-0.15	-0.08	-0.35	-0.33	0.03	-0.33
	(-2.73)	(-1.17)	(-0.65)	(-2.94)	(-2.70)	(0.23)	(-2.70)
Corr($ChgCash_{t-1}, RetDisp_{t-1}$)	0.30	-0.02	0.23	0.38	0.21	-0.01	0.33
	(2.46)	(-0.13)	(1.80)	(3.22)	(1.72)	(-0.11)	(2.78)
Corr($RetDisp_{t-1}, ExMkRet_t$)	-0.33	-0.27	0.00	-0.33	-0.33	-0.34	-0.33
	(-2.74)	(-2.18)	(0.02)	(-2.76)	(-2.73)	(-2.84)	(-2.72)

Table 11: Implications on Aggregate Accruals
In Panel A, I decompose accruals into net working capital investment and depreciation and amortization, and separately test their return predictive power in comparison with cash savings or capital investment. In Panel B, the sample is divided into two groups based on whether a firm is classified as R&D intensive, and aggregate variables are calculated separately for each group. SIC three-digit industries are sorted into quintiles based on the average R&D investment as of total assets since 1964. Firms in the top industry quintile are defined as R&D firms. Results about R&D-intensive group (Y) or not (N) are reported. t-statistics are reported in parenthesis and are corrected for autocorrelation using Newey-West method lagging three periods. *, **, *** denote statistical significance at 10%, 5%, 1% levels respectively.

(a) Aggregate accruals decomposition

	(1) $ExMkRet$	(2) $ExMkRet$	(3) $ExMkRet$	(4) $ExMkRet$	(5) $ExMkRet$	(6) $ExMkRet$
$Accruals_{t-1}$	3.252***				2.573***	0.388
	(3.50)				(3.11)	(0.46)
$NWCInvt_{t-1}$		2.966**	-1.393			
		(2.41)	(-1.37)			
$D\&A_{t-1}$		-3.440***		-0.276		
		(-3.20)		(-0.17)		
$ChgCash_{t-1}$			-3.304***			-2.829***
			(-5.01)			(-4.55)
$CapInvt_{t-2}$				-0.970	-0.602	-1.010***
				(-1.25)	(-1.43)	(-3.09)
Constant	0.213***	0.228***	0.126***	0.179***	0.246***	0.231***
	(3.90)	(3.43)	(4.88)	(3.30)	(4.14)	(4.45)
Adj R squared	0.063	0.046	0.134	0.018	0.059	0.165
Obs	55	55	55	55	55	55

(b) The heterogeneity between R&D and non-R&D groups

	(1) $ExRet_Y$	(2) $ExRet_N$	(3) $ExRet_Y$	(4) $ExRet_N$	(5) $ExRet_Y$	(6) $ExRet_N$
$Accruals_{t-1}$			2.387***	0.549	0.737	0.318
			(3.08)	(0.49)	(0.69)	(0.31)
$ChgCash_{t-1}$	-1.700***	-3.271			-1.797***	-3.598
	(-4.37)	(-1.36)			(-4.09)	(-1.45)
$CapInvt_{t-2}$					-0.832*	-1.076**
					(-1.74)	(-2.28)
Constant	0.105***	0.078***	0.163***	0.078	0.224***	0.215***
	(4.05)	(3.96)	(3.77)	(1.58)	(4.32)	(2.95)
Adj R squared	0.114	0.015	0.074	-0.016	0.161	0.026
Obs	55	55	55	55	55	55

Table 12: Horse-Race Regressions about Aggregate Accruals
Aggregate accruals and aggregate corporate savings are calculated within each size quintiles using capitalization weights. Columns 1-5 report results about size quantiles from the smallest to the largest. Column 6 reports the results using the full sample. t-statistics are reported in parenthesis and are corrected for autocorrelation using Newey-West method lagging three periods. In the last panel, piecewise correlations between aggregate cash changes and aggregate net working capital investment in each group are calculated with t-statistics reported in parenthesis. *, **, *** denote statistical significance at 10%, 5%, 1% levels respectively.

	(1) $ExRet_1$	(2) $ExRet_2$	(3) $ExRet_3$	(4) $ExRet_4$	(5) $ExRet_5$	(6) $ExMkRet$
$Accruals_{t-1}$	0.012	-0.386	-0.784	1.522	2.158***	3.252***
	(0.01)	(-0.38)	(-0.58)	(1.41)	(3.20)	(3.50)
Constant	0.107**	0.093***	0.060	0.111***	0.162***	0.213***
	(2.37)	(3.20)	(1.36)	(3.23)	(3.66)	(3.90)
Adj R squared	-0.019	-0.016	-0.011	0.006	0.043	0.063
Obs	55	55	55	55	55	55

	(1) $ExRet_1$	(2) $ExRet_2$	(3) $ExRet_3$	(4) $ExRet_4$	(5) $ExRet_5$	(6) $ExMkRet$
$Accruals_{t-1}$	-0.785	-0.971	-1.474	0.406	0.988	1.748*
	(-0.66)	(-1.07)	(-1.18)	(0.34)	(1.26)	(1.99)
$ChgCash_{t-1}$	-1.318*	-1.446***	-1.631**	-1.017**	-2.247***	-2.468***
	(-1.95)	(-3.18)	(-2.53)	(-2.56)	(-3.12)	(-3.40)
Constant	0.145***	0.152***	0.113***	0.105***	0.132***	0.180***
	(2.75)	(4.92)	(3.04)	(3.49)	(2.85)	(3.57)
Adj R squared	0.006	0.069	0.067	0.051	0.128	0.142
Obs	55	55	55	55	55	55

	(1) $ExRet_1$	(2) $ExRet_2$	(3) $ExRet_3$	(4) $ExRet_4$	(5) $ExRet_5$	(6) $ExMkRet$
$Accruals_{t-1}$	-0.828	-1.015	-1.994	0.374	-0.523	0.388
	(-0.68)	(-0.99)	(-1.11)	(0.30)	(-0.69)	(0.46)
$ChgCash_{t-1}$	-1.313*	-1.448***	-1.614**	-1.049**	-2.613***	-2.829***
	(-1.93)	(-3.17)	(-2.64)	(-2.41)	(-4.86)	(-4.55)
$CapInvt_{t-2}$	0.104	0.076	0.402	0.210	-1.131***	-1.010***
	(0.19)	(0.17)	(0.72)	(0.39)	(-3.25)	(-3.09)
Constant	0.134	0.144**	0.048	0.081	0.182***	0.231***
	(1.63)	(2.19)	(0.42)	(1.08)	(4.05)	(4.45)
Adj R squared	-0.013	0.095	0.062	0.034	0.181	0.165
Obs	55	55	55	55	55	55

	(1) $ChgCash_1$	(2) $ChgCash_2$	(3) $ChgCash_3$	(4) $ChgCash_4$	(5) $ChgCash_5$	(6) $ChgCash$
$NWCInvt_t$	-0.225	-0.153	-0.078	-0.196	-0.461	-0.455
	(-1.69)	(-1.14)	(-0.57)	(-1.47)	(-3.82)	(-3.75)

B Online Appendix

B.1 Alternative Aggregate Cash Savings Measure

As a robustness check, I construct an alternative aggregate cash savings measure by weighting firm-level scaled cash changes using lagged total assets. This approach treats the economy as a representative agent by summing up cash changes across all firms. I then examine the return predictive power of this measure across three progressively narrower samples: (i) firms with December fiscal year-ends, (ii) firms with December fiscal year-ends and listed on NYSE, AMEX, or NASDAQ, and (iii) non-financial firms with December fiscal year-ends and listed on NYSE, AMEX, or NASDAQ. Table B.1 shows that although the predictive power of the asset-weighted aggregate cash savings measure varies across samples, it remains a robust predictor of future excess market returns.

B.2 Out-of-Sample Equity Premium Prediction Tests

Goyal et al. (2024) argue that many equity premium predictors proposed in the academic literature lack robust predictive ability and re-examine 29 predictors, concluding that only two pass their in-sample, out-of-sample, and investment strategy tests. Interestingly, aggregate accruals are among the successful predictors, suggesting that aggregate cash savings may perform even better, given their stronger in-sample performance. Moreover, since aggregate cash savings and capital investment reflect distinct dimensions of the macroeconomy, it is natural to examine how the two variables jointly perform in an out-of-sample setting. This section conducts several out-of-sample tests, in the spirit of Goyal et al. (2024), using aggregate corporate savings alone and in combination with aggregate capital investment.

The first test evaluates the forecasting performance relative to a moving average benchmark using out-of-sample R^2. Following Campbell and Thompson (2008), I compute both unconstrained and constrained out-of-sample R^2, OOS-R^2 and $OOSCT$-R^2, where the latter imposes the restriction that predicted equity premia should not be negative:

$$R^2 = 1 - \frac{\sum_t (r_t - \tilde{r}_{t-1})^2}{\sum_t (r_t - \bar{r}_{t-1})^2},$$

where r_t denotes the actual excess return, $\tilde{r}_{t-1}$ the forecast based on information available at $t-1$, and $\bar{r}_{t-1}$ the historical mean at time $t-1$. p-values are calculated using the bootstrapped MSE-F statistic from McCracken (2007).[16] I evaluate two models: one with aggregate cash savings only and another including both aggregate cash savings and capital investment. The out-of-sample forecasts follow an expanding window scheme beginning five years into the sample.

The second test involves evaluating the performance of a risk-neutral investor who times her investment based on these predictors. Specifically, she chooses between zero-investment strategies that buy market indices financed with treasury bills or short indices and buy treasuries. Because the setting includes two predictors, the non-parametric decision rule used in Goyal et al. (2024) is not applicable here. Instead, I set the investment rule as follows: the investor invests at time t when $\tilde{r}_{t-1} \geq 0$ and shorts when $\tilde{r}_{t-1} < 0$.[17] Her investment performance is then compared to an unconditional strategy *all-equity-all-the-time* where equity is held long throughout the entire sample period.

Furthermore, I consider two strategies to decide investment size, scaled and unscaled. The unscaled strategy always invests $1 of capital, while the scaled strategy adjusts the position size based on an in-time Z-like score. The Z-score is calculated as the distance between the forecast and zero, $|\tilde{r}_{t-1} - 0|$, divided by the prevailing standard deviation of r_t. The scaled strategy conveys the idea that an investor is inclined to place more bets when her forecasts deviate from zero more. Her excess scaled strategy return at t relative to the

[16] See Goyal et al. (2024) for more technical information, including the details of the bootstrap procedure.

[17] Goyal et al. (2024) base the investment decision on whether an indicator X is above its median. However, this decision rule is not optimal for investors to maximize the difference between the strategy return and the benchmark return. Assume that X predicts equity premia with a positive slope, their decision rule indicates to invest if X is higher than the median. In cases where X is lower than the median, there are still chances that $\tilde{r}_{t-1}$ is positive. Therefore, shorting the equity premium overstates the strategy losses compared to the benchmark.

benchmark can be summarized as below:

$$\text{ExRet}_t = \begin{cases} 0 & \text{if} \quad \tilde{r}_{t-1} \geq 0, \\ -2|Z\text{-score}|r_t & \text{if} \quad \tilde{r}_{t-1} < 0, \end{cases}$$

where Z-score $= 1$ in the unscaled strategy.

Table B.2 presents the out-of-sample results. Panel A demonstrates that forecasting models with aggregate cash savings or capital investment significantly outperform a moving average model in terms of both OOS-R^2 and $OOSCT$-R^2. Moreover, the model combining both predictors outperforms the single-variable model, consistent with the notion that cash savings and capital investment capture complementary macroeconomic information. Notably, the $OOSCT$-R^2 values here exceed those reported for most predictors in Goyal et al. (2024). Panel B reports performance for the unscaled and scaled strategies relative to an *all-equity-all-the-time* benchmark. For the unscaled strategy, the model using cash savings alone delivers an annual return of 6.71%, or 0.92% above the benchmark. Adding capital investment improves the strategy return to 2.55% above the benchmark, with a Sharpe ratio around 0.27. Similar results are observed under the scaled strategy. While the decision rules differ from those in Goyal et al. (2024), making direct comparisons difficult, the results reinforce the out-of-sample validity of aggregate cash savings as a predictor of equity premia.

B.3 Cross-Sectional Predictive Power of Cash Savings

Several studies have examined the cross-sectional return predictive power of cash. For instance, Palazzo (2012) explores the contemporaneous relationship between cash levels and expected equity returns, finding a positive correlation. The author also reveals that cash levels have weakly positive associations with future returns, with significant long-short strategy performance results observed only for equally-weighted portfolios, but not for size-weighted portfolios. Similarly, Simutin (2010) demonstrates that firms with high excess cash holdings tend to earn positive and significant excess returns compared to firms with low excess cash. However, it is important to note that firms with different cash levels exhibit distinct risk characteristics. Research has shown that firms in R&D-intensive industries tend to hold significantly more cash than non-R&D-intensive firms (e.g., Bates et al., 2009; Begenau and Palazzo, 2021; Falato et al., 2022), and R&D investment by firms is positively associated with future stock returns (e.g., Chan et al., 2001; Chambers et al., 2002). Evaluating cash changes, rather than cash levels, provides a better way to mitigate the impact of other firm characteristics.

For this reason, the cross-sectional analysis in this section focuses on cash changes rather than cash levels. The results are presented in Table B.3. In contrast to the findings of Palazzo (2012) and Simutin (2010), this study reveals a negative predictive relationship between cash changes and future cross-sectional returns especially among the R&D-intensive firms. This discrepancy could be attributed to the fact that cash changes capture risk factors beyond the growth options embedded in cash levels.[18] Similar to the findings of Palazzo (2012), the negative predictive power of cash savings is weak, and trading on value-weighted cash savings portfolios does not yield significant returns. Furthermore, when including the investment-to-asset ratio Inv_{t-1} in these regressions, the coefficients of cash savings become insignificant, while those of Inv_{t-1} remain significant. This weak return predictive ability of cash savings in the cross-section contrasts with its strong forecasting power at the aggregate level over time, emphasizing that the predictive capacities of cash savings in these two contexts are distinct subjects of study.

[18]Although Sodjahin (2013) find that changes in the cash ratio positively predict returns in the cross section, the methodology used in that paper is questionable. The study utilizes annual accounting data but regresses monthly returns on them and reports Fama-Macbeth coefficients. Following the method in Sodjahin (2013), I also find qualitatively similar positive prediction pattern.

Table B.1: Aggregate Cash Savings and Future Excess Market Returns

I present results on the return predictive power of aggregate cash savings. $ExMkRet$ denotes CRSP excess market returns, and the corresponding $ChgCash_{t-1}$ are computed by choosing total assets at the beginning of year $t-1$ as weights. The aggregate cash savings measure is constructed under varying sample restrictions. Columns 1 and 2 report results for firms with December fiscal year-ends. Building on this sample, Columns 3 and 4 exclude firms not listed on NYSE, AMEX, or NASDAQ, while Columns 5 and 6 further exclude financial firms. t-statistics are reported in parenthesis and are corrected for autocorrelation using Newey-West method lagging three periods. *, **, *** denote statistical significance at 10%, 5%, 1% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$ExMkRet$	$ExMkRet$	$ExMkRet$	$ExMkRet$	$ExMkRet$	$ExMkRet$
$ChgCash_{t-1}$	-9.411***	-8.308**	-8.063***	-6.695*	-7.916**	-7.618*
	(-3.28)	(-2.16)	(-2.78)	(-1.83)	(-2.50)	(-1.77)
$Default_{t-1}$		0.978		3.129		3.171
		(0.21)		(0.77)		(0.72)
$Term_{t-1}$		3.363**		3.456**		4.840***
		(2.31)		(2.47)		(3.09)
$EQIS_{t-1}$		0.010		-0.020		0.053
		(0.03)		(-0.05)		(0.14)
E/P_{t-1}		1.312		1.535		1.150
		(1.15)		(1.23)		(1.07)
D/P_{t-1}		1.953		3.008		2.635
		(0.30)		(0.48)		(0.41)
B/M_{t-1}		-0.294		-0.408		-0.306
		(-1.16)		(-1.60)		(-1.39)
Constant	0.141***	0.027	0.133***	0.007	0.107***	-0.033
	(4.79)	(0.25)	(4.41)	(0.07)	(4.65)	(-0.35)
Adj R squared	0.160	0.131	0.119	0.102	0.079	0.093
Obs	55	55	55	55	55	55

Table B.2: Out-of-Sample Tests in Goyal et al. (2024)
I assess two forecasting models in this table: one that includes only aggregate cash savings and another that incorporates both aggregate cash savings and aggregate investment. Panel A evaluates the unconstrained and constrained out-of-sample R^2, $OOS\text{-}R^2$ and $OOSCT\text{-}R^2$, where the latter imposes the restriction that predicted equity premia should not be negative. The p-values, reported in parenthesis, are calculated based on bootstrapped $MSE\text{-}F$ statistics. The out-of-sample tests use expanding schemes and commence five years after the start of the sample period. In Panel B, a zero-investment strategy is considered for a risk-neutral investor who times her investment based on the forecasted equity premium in her model. The unscaled strategy always invests \$1 of capital, and the scaled strategy invests based on an in-time Z-like score. The Z-score is calculated as the distance between the forecast and zero, $|\tilde{r}_{t-1} - 0|$, divided by the prevailing standard deviation of the equity premium. The annualized strategy raw returns, benchmark buy-and-hold returns, and their difference in terms of excess returns and Sharpe ratios are reported with bootstrapped p-values in parenthesis.

(a) In-time prevailing forecasting performance

	$OOS\text{-}R^2$	$OOSCT\text{-}R^2$
ChgCash	11.39	7.52
	(0.00)	(0.01)
ChgCash & *CapInvt*	15.07	9.97
	(0.00)	(0.00)

(b) Investment performance compared to *all-equity-all-the-time*

	Unscaled Strategy				Scaled Strategy			
	Raw	Bench	Excess	Sharpe	Raw	Bench	Excess	Sharpe
ChgCash	6.71	5.79	0.92	0.07	2.89	0.80	2.09	0.21
			(0.03)	(0.06)			(0.01)	(0.00)
ChgCash & *CapInvt*	8.34	5.79	2.55	0.27	3.97	1.47	2.50	0.25
			(0.00)	(0.00)			(0.02)	(0.00)

Table B.3: Cross-Sectional Predictive Power of Cash Savings
Since few R&D firms exist before 1980, I perform annual Fama-Macbeth regressions using full sample, R&D sample and non-R&D sample starting from 1980. Inv is the investment-to-asset ratio in Hou et al. (2015), B/M is the book-to-market ratio and $Size$ is the log market capitalization. Fama-Macbeth regression results are reported in the first panel. t-statistics are reported in parenthesis and are corrected for autocorrelation using Newey-West method lagging three periods. *, **, *** denote statistical significance at 10%, 5%, 1% levels respectively. In the second panel, I report the averages of annualized value-weighted $ExRet_{vw}$ or equal-weighted excess market returns $ExRet_{avg}$ across different groups sorted by cash changes. Columns 1-5 report results about cash change quantiles from the smallest to the largest. t-statistics are reported in parenthesis.

(a) Fama-Macbeth regressions on cash savings

	(1) All	(2) R&D	(3) non-R&D	(4) All	(5) R&D	(6) non-R&D
$ChgCash_{t-1}$	-0.123***	-0.130***	-0.060	-0.038	0.008	-0.000
	(-3.32)	(-3.54)	(-0.82)	(-0.87)	(0.20)	(-0.00)
Inv_{t-1}				-0.087***	-0.141***	-0.065**
				(-3.56)	(-3.76)	(-2.68)
B/M_{t-1}	-0.003	0.015	-0.002	-0.004	0.012	-0.002
	(-0.44)	(1.14)	(-0.33)	(-0.53)	(0.92)	(-0.38)
$Size_{t-1}$	-0.028***	-0.028***	-0.027***	-0.027***	-0.026**	-0.026***
	(-3.27)	(-2.81)	(-3.34)	(-3.19)	(-2.68)	(-3.29)
Constant	0.283***	0.288***	0.266***	0.286***	0.295***	0.268***
	(4.14)	(3.72)	(3.88)	(4.20)	(3.78)	(3.97)
Avg R Squared	0.026	0.031	0.031	0.031	0.038	0.037
Obs	39	39	39	39	39	39

(b) Long-short strategy performance

Rank	1	2	3	4	5	1-5
$ChgCash$	-11.65%	-1.51%	0.25%	2.61%	21.04%	-32.69%
$ExRet_{vw}$	8.99%	7.37%	6.26%	7.22%	7.04%	1.95%
						(1.00)
$ExRet_{avg}$	14.90%	12.92%	11.29%	11.75%	10.33%	4.57%
						(2.05)