Three Essays on Asset Pricing and Behavioral Finance

by

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Abstract

This thesis consists of three essays. The first essay develops a model to study the role of Corporate Social Responsibility (CSR) costs in the cross-section of stock returns. In our CAPM-based model, we modify the standard assumptions to allow for social and environmental costs. These CSR costs are defined as the return that a CSR-violating firm has to forgo should it invest to become fully CSR compliant. Our model predicts two risk factors, in addition to the market risk premium, that represent the aggregate market-level social and environmental cost factors and, which are priced in the cross-section of stock returns. We then empirically test the implication of our pricing model by using data from MSCI ESG. In a univariate analysis, we find that the quantile portfolio with the lowest CSR (social or environmental) cost beta significantly outperforms the highest CSR cost beta portfolio. In addition, in agreement with the theoretical predictions of our model, we find negative and significant risk premiums on both the environmental and social risk factor. In other words, when investors hold a well diversified portfolio (as in the CAPM), when the level of aggregate CSR transgressions is high, investors prefer assets that tend to perform well and can serve to hedge for high market environmental and social costs.

The second essay reports the results of three experimental studies that investigate the impact of moral identity on individuals' financial decision-making. Study 1 suggests that individual moral identity is negatively related to the willingness to invest (WTI) in an "immoral" portfolio (i.e., one containing stocks in so-called "sin" industry companies). Study 2 examines the moderating effect of a return incentive and shows that individuals with a low moral identity do have a higher WTI for an immoral portfolio, but only when they are incentivized by a higher financial return. In study 3, we discover a significant three-way interaction among moral identity, financial return, and perceived physical distance between respondents and immoral companies. When immoral stocks provide a higher return incentive, individuals with low moral identity have a higher WTI, but only when they perceive themselves to be distant from the immoral company. When these individuals perceive themselves to be physically close to an immoral company, they are less sensitive to the return incentive and their WTI is lower. In sharp contrast, the WTI for

Individuals with a high moral identity is not influenced by either the return incentive or the perceived physical distance from the immoral company.

The third essay studies human capital from the perspective of *ex ante* health perception. We first construct an index to proxy health-induced changes in human capital. Specifically, we obtain search volume data of medical symptoms from Google Trends, and we follow the methodology of Da, Engelberg, and Gao, (2015). We propose that increased (decreased) search volume of medical symptoms implies an *ex ante* decline (increase) in the value of health oriented human capital. We use the inverse of our health concern index to proxy the health dimension of human capital, denoted as HHC (health-induced human capital). To test whether this *ex ante* HHC is priced in lieu of human capital on the cross-section of stock returns, we first estimate stock exposure (beta) to the HHC. We find a significant and positive return spread between the highest and lowest beta portfolios. Specifically, the highest HHC beta portfolio generates 5% - 6% more annualized risk-adjusted return than the lowest HHC beta portfolio. In addition, we run Fama and MacBeth (1973) regressions, and discover that our health index is priced in the cross-section of asset returns, and that the positive risk premium on HHC is statistically significant, controlling for multiple risk factors.

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Dedication

To my parents.

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1. General Introduction

This thesis consists of three essays on asset pricing and behavioral finance. The first two essays study the ethical decision-making from firms' perspective and individuals' perspective, respectively. Financial decisions are significantly inflected by human value on morality, meanwhile, human well-being and health conditions (e.g., the recent Covid-19 pandemic) play an important role on decision-making. In the third essay, we are motivated to study the health dimension of human capital.

In the first essay, we develop a model to study the role of CSR costs in the cross-section of U.S. stock returns. In our model, we modify the CAPM by incorporating social and environmental cost factors, which are defined as the return that the CSR-violating firms have to forgo should they choose to become fully social and environmental compliant. Our model predicts that the aggregate market-level social and environmental cost factors are both priced in the cross-section of stock returns. We then empirically test the implication of our pricing model by using MSCI ESG data. We estimate the stock exposure (betas) with respect to the aggregate CSR (social or environmental) cost factor. The univariate analysis reveals that the quantile portfolio with the lowest CSR cost beta significantly outperforms the highest CSR cost beta portfolio. In addition, we discover a negative and significant risk premium on the market-wide CSR (social or environmental) cost factor. This finding is consistent with the prediction of our model. In other words, while CSR transgressions on the market is high, investors prefer assets that tend to perform well and can serve as a hedge for the high market CSR costs.

In the second essay, we conduct three experimental studies to investigate the impact of moral identity on individuals' financial decision-making. In Study 1, we find that moral identity has a negative effect on individuals' willingness to invest (WTI) in an immoral portfolio (e.g., sin stocks). Study 2 examines the moderating effect of financial incentives on the relation between moral identity and ethical decision-making. The study result discovers that individuals with a low moral identity have a higher WTI for an immoral portfolio only when they are incentivized by a higher financial return. We then conduct Study 3 to further study the moderating effect of physical distance, and we discover a significant three-way interaction among moral identity, financial return, and physical distance between participants and immoral companies. When immoral stocks are associated with a higher return incentive, individuals with low moral identity have a higher WTI only when they perceive themselves to be physically distant from the immoral company. However, when these individuals perceive that their distance to an immoral company is short, they are more insensitive to the financial incentive, thus their WTI is lower.

Individuals' financial decisions are significantly influenced by human well-being and human health. In the third essay, we construct an index to proxy health-induced changes in human capital and study human capital from the perspective of *ex ante* health perception. Specifically, we adopt the searching information on medical concerns (provided by Google Trends) and follow Da, Engelberg, and Gao, (2015), which constructs a sentiment index using the same data source. Our health concern index is found to have a negative and significant relation with the return of stock index, and this negative impact seems to be fundamental. We then take the inverse of our health concern index to measure health-induced human capital. The empirical analysis reveals health perspective human capital is positively priced in the cross-section of stock returns, and the results are consistent to the existing literature on human capital.

2. Triple Bottom Line Asset Pricing: Theory and Evidence

2.1 Introduction

Corporate social responsibility (CSR) has been extensively studied by researchers and market participants for several decades. One aspect of CSR--socially responsible investing--affects a corporation's strategy and its agents' investment decisions. Previous research has focused mainly on the financial performance of firms that actively practice CSR. However, the evidence is contradictory. Some studies find that corporate financial performance has a positive relation with increased corporate social performance (e.g., Derwall, Guenster, Bauer and Koedijk, 2005; Filbeck, Gorman and Zhao, 2009; Wu and Shen, 2013; Bansal, Wu and Yaron, 2018). Others find a negative link between CSR and financial performance, both theoretically and empirically (e.g., Pastor, Stambaugh and Tayor, 2020; Barber, Morse, and Yasuda, 2020; Baker, Bergstresser, Serafeim, and Wurgler, 2018; Hong and Kacperczyk, 2009; Brammer, Brooks, and Pavelin, 2006; and Geczy, Stambaugh, and Levin, 2005).

While the so-called "sin stocks" (companies involved in the alcohol, tobacco, firearms, and gaming industries) are associated with a higher stock return (Hong and Kacperczyk, 2009), a well-established literature shows that firms with lower CSR rankings have higher exposure to several specific risks. These include idiosyncratic risk (Lee and Faff, 2009), boycott risk (Luo and Balvers, 2017), litigation risk (Fabozzi, Ma, and Oliphant, 2008), future crash risk (Kim, Li, and Li, 2014), and downside risk (Hoepner, Oikonomou, Sautner, Starks, and Zhou, 2020). Therefore, investors demand a higher return for holding the stocks of CSR-violating firms. At the same time, moral investors gain nonpecuniary utility from holding CSR-compliant stocks, and they are willing to accept a lower return in order to invest in socially responsible stocks (e.g., Renneboog, Horst, and Zhang, 2008; Martin and Moser, 2015; and Barber, Morse, and Yasuda, 2020). The evidence suggests that investors bear a cost for investing in socially responsible stocks. In addition, Geczy, Stambaugh, and Levin (2005) compare the optimal mutual fund portfolios constructed with or without social screens. They find the optimal portfolios with socially responsible investing constraints incur a CSR cost. The fact that responsible firms and moral investors are exposed to a socially responsible cost motivates us to study the aggregate level social cost.

Elkington (1994) identifies three elements of performance: business profit, social responsibility, and environmental impact in "win-win-win business strategies." Triple bottom line (TBL) reporting (Elkington, 1997) refers to the impact of business activity in the economic, social, and environmental realm. It is sometimes denoted as 3Ps (profit, people, and planet). TBL is an integrated framework which takes into account the sustainability terms of social and environmental dimensions when evaluating a firm's performance. (Slaper and Hall, 2011). People value social impact (Hainmueller, Hiscox, and Sequeira, 2015), and they also care about environmental issues (e.g., pollutions, carbon emission, and global warming) (Heinkel, Kraus, and Zechner, 2001). Firms increase disclosures for the environmental dimension (mandatory and voluntary; Elkington, 1994), consumers tend to purchase environmentally friendly products, and investors prefer to invest in environmentally responsible stocks.

The sustainability of the environmental dimension has been studied in various papers. Baker et al. (2018) find that investors have a preference to hold green (environmentally responsible) bonds even though green bonds are associated with a lower rate of return. Hsu, Li, and Tsou (2020) find that there is a pollution premium, namely that industries with higher toxic emissions significantly outperform industries with lower toxic emission. Bolton and Kacperczyk (2020) find that firms with higher carbon emissions achieve higher returns, and that the carbon premium has increased dramatically in recent years. All of this evidence shows that green firms and environmentally responsible investors are exposed to an environmental cost. Firms emphasizing sustainability are also exposed to both a socially responsible cost and an environmentally responsible cost.

Both social and environmental effects play a significant role in sustainable development. Social and environmental issues have become very important, and we are interested in studying the impact of firms' sustainability efforts on the cross-section of stock returns. We contribute to the literature by first developing a theoretical asset pricing model (APM) incorporating social and environmental risks, and our model predicts that the traditional market factor is altered by two risk premia demanded by investors as compensation for exposure to stochastic social and environmental costs. We further demonstrate that the uncertainty related to social and environmental costs alters the stock's market (systematic) risk. Inspired by the implications of our theory, we then proceed to empirically estimate market level traded (long-short) social and environmental factors using the MSCI ESG database and equity returns. We theoretically and empirically demonstrate that investors prefer to hold assets with positive social and environmental factor loadings to hedge with high returns during periods of high CSR costs. Consistent with the spirit of our model, we show that portfolio exposure with respect to both CSR factors is cross-sectionally priced for US stocks.

We first develop a simple model and provide a theoretical basis for incorporating social and environmental cost factors in the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965). We denote our model as the Triple Bottom Line (TBL) asset pricing model. We propose that moral investors care about social and environmental impact, and they gain utility not only from wealth generation but also from the satisfaction of holding CSR-enhancing investments. In our model, investors experience disutility to invest in "irresponsible" stocks through the channel of social and environmental costs; we define the social or environmental cost as the portion of return that the company foregoes to become socially- or environmentally-compliant. We can also think of the social (environmental) cost as the return that moral investors sacrifice in order to boycott social (environmental) violators. Our model assumes that moral investors can still invest in firms that are involved in some social (environmental) transgressions, but that the portion of the return that the firms generate from social (environmental) transgressions will be donated to social- and environmental-enhancing projects. With a negative exponential utility, our model predicts that the market-wide social and environmental cost factors are both priced in the cross-section of equity returns; in particular, the expected stock return is negatively associated with two covariance terms: (1) the covariance between the security return and the aggregate market level social cost (social cost beta); and (2) the covariance between the security return and the market wide environmental cost (environmental cost beta).

Our theory builds on the work of Pastor et al. (2020), which suggests that investors gain utility by investing in socially responsible firms and experience disutility from investing in irresponsible firms. Our model is different from Pastor et al. (2020) in two dimensions. First, in their model Pastor et al. (2020) assume that the firm's ESG characteristic is deterministic. Thus, in their model there is no factor loading associated with the firm's CSR performance. Our model considers stochastic CSR costs, which allows us to theoretically study CSR-related systematic risk. Second, Pastor et al. (2020) study CSR as a whole with no distinction between social and environmental factors, while our model stratifies the CSR cost into these two components.

By using MSCI ESG data, which provides ratings on social and environmental performance across firms, we can study the unified CSR cost factor (a factor which aggregates the cost on social and environmental concerns) and examine the social and environmental impact separately. Therefore, we test the spirit of our model in two ways: (1) the impact of the unified CSR factor; and (2) the impact of the social and environmental factors separately. To construct a unified CSR cost factor, we first quantify CSR performance using the MSCI ESG database, which provides the number of strengths and concerns for each company in each of the following categories: environment, diversity, community, products, human rights, employee relations, and corporate governance. The unified CSR score is calculated as the aggregate difference of strength and concerns across six different categories (with the exclusion of the corporate governance category) (Albuquerque et al., 2019). Each firm in the dataset of MSCI ESG is indexed to an aggregate CSR indicator, and we then sort these firms into three quantile portfolios based on their CSR score. Intersecting with two size portfolios, we obtain a six size-CSR value weighted portfolio. The CSR cost factor, denoted as IMR (irresponsible stocks minus responsible stocks), is constructed as the return differences between a low CSR rating quantile portfolio and a high CSR rating portfolio.

Next, we estimate the stock exposure to the unified market-level CSR costs (IMR) by using 60-month backward rolling regressions for all stocks listed on the American Stock Exchange (Amex), the New York Stock Exchange (NYSE), and Nasdaq. After obtaining the CSR cost betas (the coefficient estimates on the IMR variable), we construct five quantile portfolios based on the sorting of CSR cost betas to examine the cross-sectional variation of stock return in unified CSR cost beta portfolios. We find that the quantile portfolio with the lowest CSR cost beta generates a strongly significant and positive average return. The value weighted return spread between the lowest CSR cost portfolio and the highest beta quantile portfolio is 0.64% per month (7.68% per year) with a Newey-West t statistic of 1.94. We then control for well-known risk factors, and we find that the factor models cannot explain these return spreads. After controlling for five of the most common risk factors (Fama French, 2015; Hou, Xue and Zhang, 2015), the difference portfolio (High-Low) yields a monthly risk-adjusted return of 0.67% (or 8.04% annually) with a t statistic of 2.06.

Next, we examine the pricing of the unified CSR cost factor with a Fama and MacBeth (1973) regression, and we find a negative and strongly significant risk premium for the aggregate CSR cost factor. Our empirical results provide consistent evidence that our theoretical model captures the fact that the long/short CSR return-based factor is priced in equity markets. The results are also in line with the findings in the literature that sustainability is market-wide priced (Hartzmark and Sussman, 2020).

We discover that the aggregate unified CSR cost factor is priced in stock returns; specifically, the market-level CSR cost factor carries a negative premium. We then use the same approach to construct a social cost factor (IMR_S) and an environmental cost factor (IMR_E) separately. Since the variability of the environmental indicator across firms is very low from the MSCI ESG, we are not able to sort firms into three quantile portfolios based on the environmental rating. Therefore, the environmental cost is constructed from four size-environmental quantile portfolios. The social cost is constructed from six size-social quantile portfolios. The empirical results also support the prediction in our TBL asset pricing model, and both social and environmental cost factors are negatively priced in the cross-sectional equity returns. In the robustness regression, we borrow the environmental ratings in the Refinitiv ESG data to further confirm our results. The interpretation in terms of the negative risk premium on the social (environmental) cost factor is that investors demand a higher premium on stocks with a lower covariance between stock return and the market-wide social (environmental) cost. In other words, investors demand a premium for holding a stock which generates a lower return when the market social (environmental) transgression level is higher. At the same time, investors prefer stocks which perform well when social (environmental) violation in the whole market is high.

The remainder of this chapter is organized as follows: Section 2 introduces our model incorporating the CSR cost risk. Section 3 describes our data sources and methodology. Section 4 reports the empirical evidence and provides robustness results. In Section 5, we offer some concluding thoughts.

2.2 The Model

We develop a simple one-period asset pricing model incorporating a social cost and an environmental cost with CAPM. The assumptions of the traditional CAPM hold for our setting. We follow the derivation methodology of the Sentiment-CAPM Model (Gottesman, Jacoby, and Wang, 2015).

A moral investor solves the following portfolio selection problem as follows:

$$\max_{B, V_j} E[u_i(W_i, S_i, E_i\ )] \tag{1}$$

Subject to $W_{0,i} = B + \sum_{j=1}^{N} V_j$

$$W_{1,i} = r_f B + \sum_{j=1}^{N} V_j r_j$$

$$S_i = \sum_{j=1}^{N} V_j sc_j$$

$$E_i = \sum_{j=1}^{N} V_j ec_j$$

where:

u_i: investor *i*'s utility function, *i* = *1, 2, … I*.

B: the wealth portion invested in a risk-free asset

$W_{0,i}$: initial wealth of investor *i*.

$W_{1,i}$: the perceived terminal wealth of investor *i*.

r_j: fundamental return (1 + rate of return) on risky asset j, *j=1, 2, …, N*

V_j: the wealth portion invested in a risky asset j.

S_i: the social cost that investor *i* bore from the stock holding; and $S_i = \sum_{j=1}^{N} V_j sc_j$. sc_j may represent the loss of return should the firm eliminate all social transgressions to become fully social-compliant. For example, for company k, $V_k sc_k$ represents the dollar return loss should the company eliminate all social transgressions.

E_i: the environmental cost that investor *i* bore from the stock holding; and $E_i = \sum_{j=1}^{N} V_j ec_j$. sc_j may represent the loss of return should the firm eliminate all environmental transgressions to become fully environmental-compliant.

Alternatively, one can think of investors creating home-made social- and environmental-compliant companies. That is, the investor can still invest in social- and environmental-violating companies but then donate that portion of their return in social- and environmental-enhancing projects that would be foregone should the firm become fully social- and environmental-compliant.

The social and environmental costs are not directly borne by investors. Instead, these are hypothetical costs that a given firm has to invest to become fully compliant in terms of CSR. Should the firm bear these "cleanup" costs, it will inevitably pay a lower return as a result. This allows us to consider a homemade ESG strategy for a moral investor where they donate a portion of the return attributed to CSR transgression based on the degree of their morality. In our model, moral investors will still invest in CSR violating firms but can remain true to their moral values by donating a portion of the transgression-related return to social and environmental CSR-enhancing projects. Immoral investors will not make such donation and will therefore not forgo any portion of a return earned from investing in violating firm. On the other hand, righteous investors will donate the entire return portion attributed to CSR transgressions. Investors with a moral code that falls in between these two extreme cases will donate a portion of the transgression-related return that will increase with the degree of their morality. Therefore, the costs borne by firms are homogeneous, while CSR costs from investors viewpoint are heterogeneous.

Each agent *i* has exponential (CARA) utility:

$$u_i(W_i, S_i, E_i) = -e^{-A_i(W_{1,i} - m_i S_i - m_i E_i)} \tag{2}$$

where

A_i: agent i's absolute risk aversion

m_i: the morality preference parameter for investor i, which measures investor i's morality level, where $0 \leq m_i \leq 1$.

- m_i > 0: moral investors care about CSR; the higher the m_i, the lower the utility obtained from investing in firms with CSR transgressions. $m_i = 1$ for extremely moral investors, who will donate the full portion of return which accounts for the firm's CSR transgressions.
- m_i = 0: immoral investors, who only aim is to maximize their wealth and who do not care about CSR.
- $\overline{m}$: the average morality parameter across all investors, $\overline{m} = I^{-1} \sum_{i=1}^{I} m_i$. As long as at least one investor is moral, $\overline{m}$ would be strictly positive.

Let $Y_i = W_{1,i} - m_i S_i - m_i E_i$, and we assume that Y_i is jointly normally distributed across all stocks.

Since $B = W_{0,i} - \sum_{j=1}^{N} V_j$, the terminal wealth can be written as

$$W_{1,i} = r_f(W_{0,i} - \sum_{j=1}^{N} V_j) + \sum_{j=1}^{N} V_j r_j \tag{3}$$

We then write the utility function as a function of Y_i

$$u_i(Y_i) = -e^{-A_i Y_i}$$

Plugging Equation (3) into the optimization problem in (1), we have

$$\max_{B, V_j} E[u_i(W_i, S_i, E_i)] = \max_{B, V_j} E[u_i(Y_i)]$$

$$= \max_{B, V_j} E\left[u_i\left(r_f\left(W_i^0 - \sum_{j=1}^{N} V_j\right) + \sum_{j=1}^{N} V_j r_j - m_i \sum_{j=1}^{N} V_j sc_j - m_i \sum_{j=1}^{N} V_j ec_j\right)\right]$$

The first order condition is

$$E\left[u_i'(Y_i)\left(-r_f + r_j - m_i sc_j - m_i ec_j\right)\right] = 0 \qquad (4)$$

then Equation (4) can be written as

$$E[u_i'(Y_i)]E\left(r_j - r_f - m_i sc_j - m_i ec_j\right) + Cov[u_i'(Y_i), r_j - m_i sc_j - m_i ec_j] = 0 \qquad (5)$$

Given that Y_i is jointly normal, following Steins' Lemma (Cochrane, 2001), we can rewrite the second term of Equation (5) as

$$Cov\left[u_i'(Y_i), r_j - m_i sc_j - m_i ec_j\right] = Cov\left(Y_i, r_j - m_i sc_j - m_i ec_j\right)E[u_i''(Y_i)]$$

Replacing the covariance term in Equation (5), we have:

$$-\frac{E[u_i'(Y_i)]}{E[u_i''(Y_i)]}E\left(r_j - r_f - m_i sc_j - m_i ec_j\right) = Cov\left(Y_i, r_j - m_i sc_j - m_i ec_j\right)$$

Since $\frac{E[u_i'(Y_i)]}{E[u_i''(Y_i)]} = -A_i^{-1}$, the inverse of investor *i*' absolute risk aversion. We then have

$$A_i^{-1}E\left(r_j - r_f - m_i sc_j - m_i ec_j\right) = Cov\left(Y_i, r_j - m_i sc_j - m_i ec_j\right) \qquad (6)$$

Let $Y = \sum_{i=1}^{I} Y_i$, and average Equation (6) over all investors I to get

$$I^{-1}\sum_{i=1}^{I} A_i^{-1}E\left(r_j - r_f - m_i sc_j - m_i ec_j\right) = I^{-1}\sum_{i=1}^{I} Cov\left(Y_i, r_j - m_i sc_j - m_i ec_j\right)$$

The right-hand side of the above equation can be written as

$$I^{-1}Cov\left(\sum_{i=1}^{I} Y_i, \sum_{i=1}^{I} r_j\right) - I^{-1}Cov\left(\sum_{i=1}^{I} Y_i, \sum_{i=1}^{I} m_i sc_j\right) - I^{-1}Cov\left(\sum_{i=1}^{I} Y_i, \sum_{i=1}^{I} m_i ec_j\right)$$
$$= I^{-1}Cov\left(Y, Ir_j - I\overline{m}sc_j - I\overline{m}ec_j\right) = Cov(Y, r_j - \overline{m}sc_j - \overline{m}ec_j)$$

We then have

$$E\big(r_j - r_f\big)I^{-1}\sum_{i=1}^{I}A_i^{-1} - I^{-1}\sum_{i=1}^{I}A_i^{-1}m_iE\big(sc_j\big) - I^{-1}\sum_{i=1}^{I}A_i^{-1}m_iE\big(ec_j\big) = Cov(Y, r_j - \overline{m}sc_j - \overline{m}ec_j) \tag{7}$$

Defining Equation (7) for the market portfolio, we have

$$E\big(r_m - r_f\big)I^{-1}\sum_{i=1}^{I}A_i^{-1} - I^{-1}\sum_{i=1}^{I}A_i^{-1}m_iE(sc_m) - I^{-1}\sum_{i=1}^{I}A_i^{-1}m_iE(ec_m) = Cov(Y, r_m - \overline{m}sc_m - \overline{m}ec_m) \tag{8}$$

where $r_m = \sum_{j=1}^{N} x_j r_j$, $sc_m = \sum_{j=1}^{N} x_j sc_j$ and $ec_m = \sum_{j=1}^{N} x_j ec_j$, and x_j is the relative value of asset *j* in the market portfolio.

Dividing Equation (7) by Equation (8), we get

$$\frac{E\big(r_j - r_f\big)I^{-1}\sum_{i=1}^{I}A_i^{-1} - I^{-1}\sum_{i=1}^{I}A_i^{-1}m_iE\big(sc_j\big) - I^{-1}\sum_{i=1}^{I}A_i^{-1}m_iE\big(ec_j\big)}{E\big(r_m - r_f\big)I^{-1}\sum_{i=1}^{I}A_i^{-1} - I^{-1}\sum_{i=1}^{I}A_i^{-1}m_iE(sc_m) - I^{-1}\sum_{i=1}^{I}A_i^{-1}m_iE(ec_m)} = \frac{Cov(Y, r_j - \overline{m}sc_j - \overline{m}ec_j)}{Cov(Y, r_m - \overline{m}sc_m - \overline{m}ec_m)}$$

Given that Y is linear in $r_m - \overline{m}sc_m - \overline{m}ec_m$

$$\frac{E\big(r_j - r_f\big)I^{-1}\sum_{i=1}^{I}A_i^{-1} - I^{-1}\sum_{i=1}^{I}A_i^{-1}m_iE\big(sc_j\big) - I^{-1}\sum_{i=1}^{I}A_i^{-1}m_iE\big(ec_j\big)}{E\big(r_m - r_f\big)I^{-1}\sum_{i=1}^{I}A_i^{-1} - I^{-1}\sum_{i=1}^{I}A_i^{-1}m_iE(sc_m) - I^{-1}\sum_{i=1}^{I}A_i^{-1}m_iE(ec_m)} = \frac{Cov(r_m - \overline{m}sc_m - \overline{m}ec_m, r_j - \overline{m}sc_j - \overline{m}ec_j)}{Var(r_m - \overline{m}sc_m - \overline{m}ec_m)}$$

Let θ_j^S denotes an asset j's expected social cost and θ_j^E denotes an asset j's expected environmental cost. We have $\theta_j^S = \sum_{i=1}^{I}\frac{A_i^{-1}m_i}{\sum_{i=1}^{I}A_i^{-1}}E\big(sc_j\big)$ and $\theta_j^E = \sum_{i=1}^{I}\frac{A_i^{-1}m_i}{\sum_{i=1}^{I}A_i^{-1}}E\big(ec_j\big)$ indicating the asset *j*'s expected social and environmental cost across all individual investors with different morality parameter m_i, weighted by the inverse of investor *i*'s absolute risk aversion level A_i. It implies that investors with a lower risk aversion level (a higher A_i^{-1}) and a higher morality level (a higher m_i) are associated with a higher expected social and environmental cost compared to investors with a higher risk-aversion and a lower morality level. In other words, a less risk-averse investor holds a larger portion of risky assets, and the return they gain from assets involved in social and environmental transgressions is higher. Thus, they will donate more money to social and environmental-compliant projects while these investors have a higher morality level. In addition, $\theta_m^S = \sum_{i=1}^{I} \frac{A_i^{-1} m_i}{\sum_{i=1}^{I} A_i^{-1}} E(sc_m)$, $\theta_m^E = \sum_{i=1}^{I} \frac{A_i^{-1} m_i}{\sum_{i=1}^{I} A_i^{-1}} E(ec_m)$ represent the expected aggregate social and environmental cost in the market portfolio.

Rearranging the above equation, we obtain

$$E(r_j - r_f) - \theta_j = [(r_m - r_f) - \theta_m] \frac{Cov(r_m - \bar{m}sc_m - \bar{m}ec_m, r_j - \bar{m}sc_j - \bar{m}ec_j)}{Var(r_m - \bar{m}sc_m - \bar{m}ec_m)} \tag{9}$$

Where $E(r_j - r_f) - \theta_j^S - \theta_j^E$ and $E(r_m - r_f) - \theta_m^S - \theta_m^E$ indicate the social and environmental cost adjusted risk premium on stock *j* and the market portfolio, respectively. Let us now denote asset returns net of social and environmental cost as $r_j^* \equiv r_j - \theta_j^S - \theta_j^E$ and $r_m^* \equiv r_m - \theta_m^S - \theta_m^E$, for stock *j* and the market portfolio, respectively. Then, Equation (10) below is our asset pricing model adjusted for social and environmental costs.

$$E(r_j^* - r_f) = [E(r_m^* - r_f)] \left\{ \frac{Cov(r_j^*, r_m)}{Var(r_m^*)} - \bar{m} \frac{Cov(r_j^*, sc_m)}{Var(r_m^*)} - \bar{m} \frac{Cov(r_j^*, ec_m)}{Var(r_m^*)} \right\} \tag{10}$$

Our model consists of three factor components: the first component measures the market beta, the second component represents the social cost beta, which is measured by the stock exposure to the aggregate social cost factor sc_m, and the third component represents the environmental cost beta, which is measured by the stock exposure to the aggregate environmental cost factor ec_m.

Our model in Equation (10) implies certain patterns at the cross-section of returns. Specifically, firms with returns that are negatively correlated with social or environmental costs are expected to have a higher return premium. Next, we empirically test cross-sectional patterns in returns as related to understandings we gain from our theoretical model with respect to social and environmental costs. We would like to emphasize that we do not directly test the theoretical model, rather we focus on testing the intuition of our theory which reflects an alteration to the factor structure as well as the factor loadings caused by stochastic CSR transgressions.

Our model suggests that the market social and environmental costs are both priced through the factor loading. The economic mechanism for the pricing of CSR cost is illustrated by the hedge explanation: investors expect an extra premium for holding a security which tends to perform poorly when the social or environmental costs in the market are high. In other words, at such times, investors prefer assets that tend to pay a higher return to hedge against the high market social and environmental costs.

2.3 Data and Methodology

2.3.1 Data

We obtain the CSR data from the MSCI ESG database (MSCI, formerly known as KLD Research and Analytics Inc.), which provides environmental, social, and governance (ESG) performance indicators for each company. The indicators from MSCI ESG are evaluated on the basis of seven categories, including diversity, environment, community, products, employee relations, human rights, and corporate governance. The MSCI ESG lists strengths and concerns for each company annually on each of the seven categories. Following Kim, Li and Li (2014) and Albuquerque, Koskinen, and Zhang, (2019), we aggregate the binary components for each category in firm level and use the difference of strength and concerns to represent the categorical indicator. The firm level score for the social indicator is the aggregate of scores across five social categories: community, diversity, products, employee relations, and human rights. The environmental indicator contains only one category: environment, which is determined by binary variables. Therefore, there is very little variability in environmental scores across companies, and sorting stocks into more than two portfolios is not feasible. We propose to test the unified factor using the MSCI ESG dataset as well, so we also calculate a unified CSR indicator for each firm, which is a unified CSR score across social and environmental categories.

In the robustness regression of examining social and environmental separately, we propose an alternative data source: the Refinitiv. This dataset, formerly known as Thomson Reuters, provides ESG ratings covering three pillars (social, environmental, and governance) in 10 categories for the sample period between 2002 and 2018. The Refinitiv ESG dataset uses three categories (e.g., resource use, emissions, and innovations) to determine the environmental indicator instead of the single environmental component in the MSCI ESG. The Refinitiv ESG data are also used in the CSR literature by Esteban-Sanchez et al. (2017) and Gonenc & Scholtens (2019). In addition, the variables in each category are continuous rather than binary, providing more variability across stocks and allowing us to construct an environmental factor using this dataset. While the Refinitiv ESG dataset also provides information on the social factor, we choose to retain the MSCI ESG social indicator since it includes an additional component (diversity) beyond the four included in Refinitiv (community, employee relations, human rights, and product). It is important to include a diversity component while constructing the social factor, since the evidence shows that diversity has a significant impact on firm performance and equity returns. (e.g., Richard, 2000; Carter, Simkins and Simpson, 2003; Adams and Ferreira, 2009).

The stock returns and company information are obtained from the Center for Research in Security Prices (CRSP) and from Compustat. We exclude all financial firms and utility firms (SIC codes between 6,000 and 6,999 and between 4,900 and 4,999, respectively). In addition, we eliminate share price less than $5 in order to exclude illiquid stocks, and we require a minimum of 36 monthly observations over the past 60 months of data. To obtain the market-level CSR cost factor, we merge the stock data and CSR data by matching the year-end CSR data for year $t-1$ with monthly returns from July of year t to June of year $t + 1$. For example, the returns for June 2005 are ranked based on the CSR data listed for 2003, while the returns for July 2005 are ranked based on the CSR data for 2004. The same matching procedure is used for the year-end financial statement data and return data as well.

We use the MSCI ESG dataset for the sample period 2003-2018. However, the MSCI ESG is available starting from 1991. For the period 1991-2001, this index includes only 400 ESG compliant stocks and it does not have a broad representation of ESG violators. However, it is important to include ESG violators since it is required for building market-wide ESG factors that should be inclusive of all firms with a wide variability of ESG ratings. In 2001, the MSCI ESG added 1000 stocks to the index, but those were exclusively large stocks which do not provide adequate market representation. In 2003, the MSCI ESG included the USA IMI index, which includes 2400 large, mid, and small cap US companies. Therefore, starting in 2003 the MSCI ESG database provides an adequate coverage of stocks with different market caps as well as large variations in ESG compliance. Matching the CSR data over sample periods between 2003 and 2018 with financial data gives us monthly sample data runs from July 2004 to December 2019. Table 2.1 summarizes the mean, median, standard deviation (Std. Dev.), number of observations, 1st percentile (P1), 25th percentile (P25), 75th percentile (P75), and 99th percentile (P99) for variables in our sample data. Panel A provides the descriptive statistics of firm characteristics for firms listed in the MSCI ESG dataset. There are 20,362 firm-year CSR observations. A positive unified CSR score of 0.221, suggests that, overall, firms have slightly higher CSR strengths than concerns.

2.3.2 The Unified CSR Cost Factor

We sort all firms from the MSCI ESG data based on the CSR index into three portfolios. Portfolio one contains the lowest 30% quantile, portfolio two has the 30%-70% quantile, and portfolio three includes the companies in the top 30% quantile. We also rank firms into two size portfolios based on market values using median NYSE market equity data (Fama and French, 1992). CSR portfolios and size portfolios are all constructed at the end of each June. Following size and value portfolio construction (Fama and French, 1993), we obtain six size-CSR value-weighted portfolios using the intersection of two size and three CSR quantile portfolios.

To empirically test the effect of the aggregate market CSR cost factor, we construct a factor to measure the aggregate market CSR cost, $IMR = \frac{1}{2}\left(\frac{S}{L} + \frac{B}{L}\right) - \frac{1}{2}\left(\frac{S}{H} + \frac{B}{H}\right)$ where S

denotes small market value, *B* represents big market value, *H* denotes a high CSR ranking, and *L* denotes a low CSR ranking. The CSR cost variable (IMR) represents irresponsible stock returns minus responsible stock returns. The higher the value of IMR, the higher the cost should be for CSR-violating firms to become fully CSR-compliant in the market as a whole. Panel B of Table 2.1 shows the aggregate CSR cost factor (IMR) over time. An average IMR over time of 0.298 implies that firms with CSR transgressions perform better than fully CSR-compliant firms. Also, it implies CSR-violating firms need to forego an average of a 3.576% return annually to blot out their CSR transgressions.

2.3.3 Social and Environmental Cost Factors

To empirically test the spirit of our model, we also construct separate social cost and environmental cost factors by following the same procedure as in section 1.3.2 Due to the low variability of the environmental indictor, we can only sort firms into two portfolios instead of three portfolios based on environmental ratings. Therefore, we construct a four size-environmental value-weighted portfolio using the intersection of two size and two social quantile portfolios. We also develop the social factor using a four size-social value-weighted portfolio. We then use IMR_S and IMR_E to denote the market-level social and environmental cost factors. IMR_S indicates the return difference between socially irresponsible stocks and socially responsible stocks, while IMR_E indicates the return difference between environmentally irresponsible stocks and environmentally responsible stocks.

Table 2.2 presents the correlations between the unified CSR cost factor (IMR), social cost factor (IMR_S), environmental factor (IMR_E) and other common risk factors, such as the market factor (MKT), size factor (SMB), the value factor (HML), the momentum factor (UMD), the profitability factor (RMW), the investment factor (CMA), and the liquidity factor (LIQ). Not surprisingly, the unified CSR cost factor positively and significantly correlates with the social and environmental cost factors. In addition, the unified cost factor has a positive correlation with UMD, and a negative correlation with CMA.

2.3.4 Firm Characteristics

We control for several firm characteristics in our empirical analysis. Following Fama and French (1992), we calculate firm size (denoted as Size) by taking natural logarithm on market equity, which is computed as the product of the price per share and the number of shares outstanding The book-to-market ratio (BM) at year t is calculated as the ratio of the book value of stockholder equity at the end of the fiscal year, t −1, to the market value at December of year t−1. Momentum (MOM) is calculated as the cumulative return over past 11 months (Jegadeesh and Titman, 1993). We measure a stock's monthly idiosyncratic volatility as the standard deviation of daily residuals obtained from the three-factor model of Fama and French (1993) within a month (Ang, Hodrick, Xing, and Zhang, 2006). Stock *i*'s monthly illiquidity, denoted ILLIQ, is measured in Equation (11). First, we estimate the ratios of the absolute security *i*'s return to the trading volume (in dollars) on a daily basis, then the average of daily ratios within a month t is used to presents ILLIQ at time t (Amihud, 2002).

$$ILLIQ_{i,t} = avg(\frac{|R_{i,d}|}{VOL_{i,d}}) \tag{11}$$

where $R_{i,d}$ represents the return of stock *i* on day *d*, and $VOL_{i,d}$ indicates the trading volume (in dollars) for stock *i* on day *d*. Then the measure of illiquidity is scaled by 10^6.

2.3.5 Methodology

To examine the impact of CSR cost on the cross-section of stock returns, we first estimate the stock exposure to our CSR cost factors. We follow the approach taken in previous asset pricing papers (e.g., Ang, et al., 2006; Bali, Brown and Tang, 2017). This involves regressing individual monthly stock excess return of all stocks trading on the New York Stock Exchange (NYSE), American Stock Exchange (Amex), and Nasdaq on market excess return and the aggregate CSR cost variable (IMR). The regression is conducted on a monthly basis, and the regression equation is as follows.

$$\begin{aligned} r_t^i = \beta_0 + \beta_{CSR}^i IMR_t + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t \\ + \beta_{RMW}^i RMW_t + \beta_{CMA}^i CMA_t + \varepsilon_t^i \end{aligned} \tag{12}$$

where *MKT* is the excess return of the market portfolio, and *IMR* is the aggregate level CSR factor, which is constructed based on the difference of returns between low and high CSR ranking portfolios. We also control for size, value, profitability, and investment factors; these factors are obtained from Kenneth French's data library. β_{MKT}^{i} is the market beta for stock *i*, and β_{CSR}^{i} is the exposure of individual stocks on the aggregate CSR cost. We run monthly backward rolling regressions of excess stock returns on risk factors with a 60-month fixed window, and each regression is conducted with no less than 48 monthly observations. Although we restrict the cross-sectional factors to Fama-French five factors to minimize the noise in Equation (12), we control momentum and liquidity later to examine how the aggregate CSR cost is priced in equity returns.

2.4 Empirical Analysis

We examine the role of the CSR cost on the cross-section of stock returns in two ways: (1) by testing the impact of the unified CSR factor; and (2) by testing the social and environmental factors separately as described in our TBL asset pricing model. In subsection 4.1, we conduct several tests to study the unified CSR factor, which is constructed based on five social categories and one environmental category in the MSCI ESG dataset. In subsection 4.2, we study the social and environmental factors separately. We follow the same test procedure described in subsection 4.1 to examine the pricing of social and environmental factors. We also run robustness regressions by constructing the social factor from the MSCI ESG and the environmental factor from the Refinitiv ESG.

2.4.1 Unified CSR Factor Analysis

To test the unified CSR cost factor empirically, we first start with univariate portfolio analysis, and then present bivariate portfolio analyses that control for well-known firm characteristics. Next, we conduct Fama-MacBeth (1973) regressions to discover the pricing of the aggregate unified CSR cost factor on the cross-section of equity returns. Finally, we present additional robustness regression results.

2.4.1.1 Univariate Portfolio Analysis

To explain the variation in stock returns because of exposure to the market-level unified CSR cost factor, we examine univariate portfolios sorted by the unified CSR cost betas. We obtain the factor loadings (β_{CSR}^{i}) on the unified market level CSR cost factor (IMR) from the multivariate regression in Equation (12). Table 2.3 summarizes the results of the univariate portfolio analyses for both value-weighted and equal-weighted portfolios. For each month, we sort firms into five quantile portfolios based on the CSR loadings (β_{CSR}^{i}). Firms in portfolio Low have the lowest CSR cost loadings and firms in portfolio High have the highest CSR cost betas. Columns 1-3 in Table 2.3 present the average firm size, book-to-market ratio, and CSR cost beta in each quantile portfolio. There is no significant difference in firm size across the five portfolios, and the book-to-market ratio is slightly higher in the highest beta portfolio. Next, we calculate equal-weighted and value-weighted portfolio returns, and the average returns across five portfolios are reported in Column 4. We observe a significant discrepancy in the average returns across five portfolios, with the monthly equal-weighted average return decreasing from 1.60% to 1.19% moving from the lowest quantile portfolio to the highest quantile portfolio. The average returns spread between the highest and lowest beta portfolio is -0.41% per month, suggesting that being long on a lowest CSR beta portfolio and short on a highest portfolio generates a 4.92% return per year.

In each of the five quantile portfolios formed on the unified CSR cost betas, we run regressions on common risk factors, including the market factor, size and value factors (Fama and French, 1993), the momentum factor (e.g., Jegadeesh and Titman, 1993; Carhart, 1997), investment and profitability factors (Fama and French, 2015), and the liquidity factor (Pastor and Stambaugh, 2003). The intercept of each regression (alpha) is the risk-adjusted return. The average risk-adjusted returns (alphas) for different asset pricing models are also reported in Table 2.3.

The last row of Table 2.3 summarizes the magnitude of average return and factor-adjusted return differences between the highest and lowest beta portfolios (High-Low). A large positive risk-adjusted return is associated with the lowest CSR cost portfolio, and these returns are not explained by the Fama-French three-factor (FF3) model, the Carhart four-factor (Carhart4) model, the Fama-French five-factor (FF5) model, and the FF5 with momentum and liquidity (FF5+ML) model. Also, the alphas in the difference portfolio (High-Low) are negative and statistically significant for all factor models. In the last column of Table 2.3 (FF5+ML), the lowest equal-weighted β_{CSR} portfolio generates a significantly higher factor-adjusted return of 0.52% per month than the highest CSR cost portfolio. In general, Table 2.3 suggests that low CSR cost beta portfolios significantly outperform the high beta portfolios, and CSR cost loadings have a significant impact on equity returns.

2.4.1.2 Portfolios Analysis Controlling for Firm Characteristics

Following Ang et al. (2006), we also conduct a bivariate portfolio analysis to control for different firm characteristics. To control for firm size, we first construct five quintile portfolios based on firm market capitalization. Within each size quintile, we further sort stocks into five portfolios based on their CSR cost beta. All portfolios are balanced monthly. We then calculate the average return across five size quantiles for each of five CSR cost beta portfolios. Now each CSR cost portfolio contains all size dispersions. The same method is also applied to control for other firm characteristics (e.g., BM, momentum, and illiquidity). Panels A through Panel D of Table 2.4 present the empirical results for the equal-weighted portfolio analysis controlling for size, BM, momentum, and illiquidity, respectively.

We observe a consistent result in Table 2.4 compared to the univariate portfolio analysis in Table 2.3. For example, Panel A indicates that five beta portfolios exhibit a cross-sectional variation in the average returns, and the returns decrease monotonically from the lowest beta portfolio (1.63% per month) to the highest beta portfolio (1.17% per month). The return spreads in the difference portfolio (High-Low) are negative and significant in all panels except Panel B. We then obtain risk-adjusted returns from five factor models, and the alpha spreads in High-Low portfolios across different models are significantly negative in all four Panels. The value-weighted portfolio analysis provides consistent results with equal-weight portfolio analysis (they are not reported in this chapter). Table 2.4 concludes that the outperformance of low beta portfolios is robust after controlling for different firm characteristics.

2.4.1.3 Fama-MacBeth Regressions

Higher returns are linked to portfolios with lower loadings on market-level CSR cost, and these average returns cannot be explained by well-known risk factors. We further examine the pricing of the CSR cost factor by running a two-stage Fama-MacBeth (1973) regression. Following Ang et al. (2006), we first construct 25 value-weighted quantile portfolios sorted on market betas (β^i_{MKT}) and CSR cost betas (β^i_{CSR}). We sort stocks based on β^i_{MKT} obtained from the CAPM model, while regressing excess stock returns on excess market returns only. We then obtain the β^i_{CSR} using equation (12). Stocks are ranked first into 5 β^i_{MKT} quintile portfolios and then within each β^i_{MKT} quantile portfolio, we rank stocks into 5 β^i_{CSR} quintiles.

The Fama-MacBeth (1973) regression is described in Equation (13):

$$r^i_t = \lambda_0 + \lambda^i_{MKT}\beta^i_{MKT} + \lambda^i_{CSR}\beta^i_{CSR} + \lambda^i_X\beta^i_X + \varepsilon^i_t \qquad (13)$$

where β^i_{MKT} and β^i_{CSR} are factor loadings of a market factor (excess market return) and the CSR cost factor for portfolio *i*. λ^i_{MKT} and λ^i_{CSR} are estimates of risk factor premiums. β^i_X indicates the factor loadings on other factors which have explanatory power on stock returns, such as the size factor, value factor, momentum, liquidity, investment, and profitability factors. λ^i_X represents the price premium of risk factor *X*. The two-stage Fama-Macbeth (1973) regression allows us to determine the premium expected for exposure to risk factors over time. In the first stage, we run time series regressions for each of 25 portfolios to estimate the factor loadings on each factor. In the second stage, we estimate the cross-sectional risk premium on factor loadings, then average the risk premiums over time to examine the statistical significance of these time series averages of risk premiums.

Table 2.5 presents the regression results of estimating the price of all risk factors. First, we observe that the market, size, and value factors all perform poorly after we include CSR cost factors in the regression.[1] In contrast, the coefficient estimate of IMR is negative and statistically significant in all models. In addition, the economic impact of the CSR cost factor is significant and large. Controlling for FF3 risk factors, while a stock move from

[1] This result is consistent with the recent asset pricing paper of Ang et al. (2006), which constructs an aggregate volatility factor and study the pricing of the volatility risk. This paper discovers that the aggregate volatility factor carries a negative and significant risk premium, while other well-known risk factors (e.g., MKT, SMB, HML, UMD and LIQ) have no significant impact on cross-section of asset returns.

the lowest β_{CSR} portfolio to the highest β_{CSR} portfolio, the monthly average returns will decrease from 0.78% ($\beta_{CSR} \times \lambda_{CSR} = -1.59 \times -0.488$) to -0.89% ($\beta_{CSR} \times \lambda_{CSR} = 1.82 \times -0.488$), which is a difference of 1.67% per month. The negative and significant relation between the IMR factor loading and portfolio returns indicates a negative risk premium for the aggregate CSR cost factor.

Our empirical evidence suggests that the aggregate market CSR cost factor is priced in a cross-section of average stock returns. Investors demand a premium to invest in stocks with a lower covariance between the aggregate market-level CSR cost and the return on this asset. In other words, investors prefer to purchase stocks with a higher CSR cost beta, which are stocks that pay higher returns when the market level CSR cost is high. Since higher market-side CSR cost implies that the overall market CSR transgression level is higher, investors prefer a high beta portfolio to hedge against CSR violation in the whole market.

2.4.1.4 Robustness: Orthogonalized CSR Cost

We conduct some additional robustness regressions to further examine the impact of aggregate CSR cost on cross-section of stock returns. The correlations in Table 2.2 suggest that our unified CSR cost factor is highly correlated with the risk factors UMD and CMA. Thus, someone may argue that the pricing of our CSR cost factor can be explained by other risk factors due to the correlation. Therefore, we orthogonalize our unified CSR cost factor against UMD and CMA. The orthogonalized IMR is calculated as the sum of the intercept and residual from regressing IMR on UMD and CMA. We then estimate the individual stocks' loadings on the orthogonalized IMR (beta on the unified CSR cost factor). After that, we conduct a univariate portfolio analysis. The orthogonalized IMR is highly correlated with the original IMR, and the univariate portfolio analysis results are consistent with Table 2.3, thus, results are not reported in this chapter.

2.4.1.5 Robustness: Alternative CSR Cost Betas

To obtain individual stocks' loadings on the market level CSR cost, we regress a stock's excess return on the CSR cost factor (IMR) while controlling for risk factors in the FF5 model (Equation (12). In this section, we run regressions using Equation (14) and obtain CSR cost betas by controlling for additional risk factors (momentum and liquidity).

$$r_t^i = \beta_0 + \beta_{CSR}^i IMR_t + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \beta_{RMW}^i RMW_t + \beta_{CMA}^i CMA_t + \beta_{UMD}^i UMD_t + \beta_{LIQ}^i LIQ_t + \varepsilon_t^i \quad (14)$$

We then conduct a univariate portfolio analysis based on this adjusted CSR cost beta; results are reported in Table 2.6. The portfolio with the lowest CSR cost loading generates a significantly positive risk-adjusted return, and alphas decrease monotonically from the lowest beta portfolio to the highest beta portfolio for all risk conventional models. In addition, the statistical significance of the alpha spread in the High-Low portfolios across different risk models remains robust in both equal-weighted and value-weighted portfolios.

2.4.2 Social and Environmental Factors Analysis

We study social and environmental costs separately to directly examine the theoretical prediction in our TBL asset pricing model. The social cost factor and environmental cost factor are constructed separately as described in section 1.3.3.

2.4.2.1 Univariate Portfolio Analysis

To conduct a univariate portfolio analysis, we first estimate the factor loadings (β_S^i and β_E^i) on the social cost factor and the environmental cost factor. To obtain the factor exposure on the market- level social cost factor, we run a 60-month backward rolling regression and regress the individual stocks' excess returns on the social cost factor (IMR_S), controlling for the commonly used FF5 risk factors. We then use the same approach to estimate the exposure of individual stocks to the environmental factor (IMR_E). The univariate portfolio analyses for social beta portfolios and environmental beta portfolios are illustrated in Table 2.7 and Table 2.8, respectively.

Panel A of Table 2.7 reports the equally weighted portfolio returns, and the portfolio average of stock exposure on social factor increases from -2.01 in the lowest beta portfolio to 2.32 in the highest beta portfolio. The average returns (column 4) and risk-adjusted returns (columns 5-9) decrease monotonically from the lowest β_{Social} portfolio to the highest β_{Social} portfolio. Even through the portfolio average return in the High-Low difference portfolio is not statistically significant, the risk-adjusted returns are strongly significant after controlling for common risk factors. This evidence means that alpha spreads are significantly different from zero in the difference portfolio, and that the common risk factors, including FF5 risk factors, are not sufficient to explain the substantial return spread across the social beta-sorted portfolios. Panel B of Table 2.7 reports the analysis based on value-weighted portfolios. The returns in the value weighted portfolio analysis do not decrease monotonically, but the average return difference in the difference portfolio remains statistically significant at the 5% level. In addition, the risk-adjusted return spreads in the High-Low portfolio are significant with at the 10% level after controlling for different risk factors.

Table 2.8 also provides empirical evidence for the univariate portfolio of stocks that are sorted based on their exposure to the market-wide environmental cost. The result consistently confirms our model's implication: the environmental beta has a negative and significant relation with the expected stock returns. The average returns and factor-adjusted returns in the difference portfolios (High-Low) are statistically significant across equal-weighted portfolio analysis (Panel A) and value-weighted portfolio analysis (Panel B). The return spread between β_{Env} and low β_{Env} portfolios is mainly attributed to the outperformance of the low beta portfolio, suggesting that investors demand extra premiums for holding stocks having a negative correlation with market-level environmental transgressions.

2.4.2.3 Fama-MacBeth Regressions

Our theoretical model (TBL asset pricing model) implies that both social and environmental cost factors are priced in the cross-section of equity returns. We conduct a standard two-stage Fama-MacBeth methodology to investigate the pricing power of social and environmental cost factors. We first construct 25 value-weighted portfolios based on the sorting on market beta and social beta. In the first stage, we run portfolio level time series regressions to obtain factor loadings (betas) on risk factors. Then in the second stage, we regress excess return on betas cross-sectionally to estimate beta coefficients for each month; the regression is presented in equation (15). Then we average estimated beta coefficients across time to obtain our estimated risk premium on risk factors.

$$r_t^i = \lambda_0 + \lambda_{MKT}^i \beta_{MKT}^i + \lambda_{Social}^i \beta_{Social}^i + \lambda_{Env}^i \beta_{Env}^i + \lambda_X^i \beta_X^i + \varepsilon_t^i \qquad (15)$$

The estimate of average beta coefficients (risk premium) is shown in Table 2.9. In column 1 of Table 2.9, we test the impact of social and environmental factors using the CAPM. The estimated risk premium on social cost factor is -0.322 per month with a t statistic of -1.83 corrected for Newey-West estimation. The environmental factor carries a risk premium of -0.392 per month with a t statistic of -2.17. When controlling for FF3 factors and Carhart 4 factors in columns 2-3, the average of coefficient estimates for the social and environmental cost factors remain statistically significant at the 10% level and 5% level, respectively. However, the social cost factor is not significant in columns 6-7 when we test with FF5 risk factors, and FF5 with additional momentum and liquidity factors. The risk premium for the environmental cost factor is statistically significant at the 5% level in all models, suggesting a strong environmental impact on the cross-section of stock returns. The Fama-MacBeth regression provides evidence that both social and environmental costs carry a negative and significant risk premium, confirming the strong pricing power of social and environmental impacts.

2.4.2.3 Robustness Regressions: Refinitiv Dataset

Due to the low variability in the environmental indicator of the MSCI ESG dataset, we borrow the environmental indicator from the Refinitiv ESG dataset. The Refinitiv ESG contains three environmental ratings (resource use, emissions, and innovations), and the variability is large enough to split firms into three portfolios. Therefore, we construct six size-environmental equal-weighted portfolios using the intersection of two size and three social quantile portfolios to estimate the environmental cost factor (IMR_E). We keep the social cost factor from the MSCI ESG dataset; it is constructed using six size-social cost quantile portfolios in the robustness regression. Table 2.10 reports the univariate portfolio analyses. Panel A of Table 2.10 presents the univariate portfolio of stocks sorted by social cost beta, and Panel B reports the univariate portfolio stocks sorted by environmental cost beta. The results are consistent with Tables 2.7 and Table 2.8, confirming that both social cost beta and environmental cost beta are negatively associated with stock returns.

2.5 Conclusion

In this chapter, we develop an asset pricing model by incorporating a social cost factor and an environmental cost factor. In our model, moral investors care about the social and environmental impact on sustainable development, and they gain utility not only from maximizing wealth but also from correcting social and environmental transgressions. To regulate social (environmental) transgressions, moral investors carry a social (environmental) cost, which is defined as the return that the social-violating firms should forego to become fully social-compliant (environmental-compliant). In our model, moral investors could still invest in socially (environmentally) irresponsible firms, but they will donate part of their gain associated with social (environmental) transgressions to social-(environmental)-enhancing projects. The level of donations will be determined by a morality coefficient. The higher the morality coefficient, the higher the donations the investor will make to enhance overall social (environmental) performance. Assuming a negative exponential utility, our model predicts that the aggregate market social and environmental cost factors are both priced in the cross-section of stock returns. Specifically, the expected returns are negatively associated with two additional covariance terms: covariance between an individual firm's return and the market-level social cost, and covariance between a firm's return and the market-level environmental cost.

In the empirical analysis, we propose two ways to test the impact of CSR: (1) test the unified CSR cost factor; and (2) test the social and environmental cost factors separately. Therefore, we qualify the market-wide CSR cost using three factors: a unified CSR cost factor (denoted as IMR), a social cost factor (denoted as IMR_S) and an environmental cost factor (denoted as IMR_E). While the unified CSR cost factor is constructed based on the return difference between the lowest CSR score quantile portfolio and the highest CSR score portfolio, the social (environmental) cost factor is developed by using the return spread between low social (environmental) rating quantile portfolios and high social (environmental) rating portfolios. To test the unified CSR cost factor, we first estimate the stock exposure to the market CSR factor by regressing the individual stock excess return on the CSR cost factor, controlling for well-known risk factors. Consistent with the prediction of our model, we discover that the portfolios formed on the unified CSR cost loadings explain the variation of cross-sectional stock returns. Specifically, low and negative CSR cost beta portfolios generate a significantly higher return than high and positive CSR cost beta portfolios. Controlling for market, size, value, momentum, profitability, investment, and liquidity factors, the average risk-adjusted returns in the High-Low difference portfolio remain negative and significant. We then examine the pricing of the CSR cost factor using the Fama-MacBeth (1973) two-stage regressions and discover that the unified market-level CSR cost factor carries a negative risk premium. The risk premium is not only statistically significant but also economically important.

We then test social and environmental factors separately. The empirical results in the univariate portfolio analyses and the Fama-MacBeth regression are both consistent with our model's prediction, confirming the strong pricing power of the social and environmental cost factors. Therefore, we conclude that the long/short return-based social cost factor and environmental cost factor are both priced in asset pricing.

2.6 Connection to Chapter 3

This chapter studies the impact of CSR cost on cross-section of stock returns. The CSR cost is a hypothetical cost ("cleanup" cost) that a given firm has to invest to become fully compliant in terms of CSR. The costs borne by firms are homogeneous, however, the CSR cost from individual investor viewpoint is heterogeneous due to their differences in human morality. Higher the morality level suggests investors are more moral, therefore, a higher portion of CSR transgression related return will be donated to CSR enhancing project.

Chapter two aimed to study the firm level CSR engagement and its impact on asset pricing. Our theoretical model implies that individuals' morality parameter plays an important role on asset pricing. In next chapter, we focus on studying the individuals' differences in morality. Specifically, we conduct experimental studies to examine how individual's morality value affects their financial decision making.

Table 2. 1 Summary Statistics

Table 2.1 reports the mean, median, standard deviation (Std. Dev.), 1st percentile (P1), 25th percentile (P25), 75th percentile (P75), and 99th percentile (P99) for each variable. Panel A summarizes the firm characteristics for firms listed in the MSCI ESG dataset, and the CSR score indicates the average CSR indicator across all firms. Variable Momentum (MOM), Illiquidity (ILLIQ), and Idiosyncratic volatility (Idio Vol) are calculated based on percentage returns. Panel B reports the market-level unified CSR cost factor (IMR), social cost factor (IMR_S), and environmental cost factor (IMR_E). IMR (irresponsible minus responsible) is constructed by the return difference of portfolios between low CSR score firms and high CSR score firms.

Panel A: Summary Statistics for ESG Firm Characteristics								
	Mean	Median	Std. Dev.	Num of Obs.	P1	P25	P75	P99
CSR Score	0.221	0.000	2.258	20,362	-4	-1	1	8
Size	7.542	7.326	1.535	222,842	4.851	6.429	8.430	11.984
BM	0.473	0.357	0.501	222,842	-0.154	0.197	0.613	2.280
MOM	14.846	13.865	37.098	222,147	-72.926	-5.295	33.157	119.028
ILLIQ	0.749	0.110	5.024	222,842	0.001	0.027	0.416	9.788
Idio Vol	1.690	1.427	1.144	214,855	0.446	0.996	2.056	5.605
Panel B: Summary Statistics of CSR Cost Factor								
Unified CSR Cost Factor (IMR)	0.298	0.200	1.409	185	-3.375	-0.513	1.225	4.236
Social Cost Factor (IMR_S)	0.205	0.255	1.125	185	-2.645	-0.547	0.826	3.309
Environmental Cost Factor (IMR_E)	0.079	0.150	1.299	185	-3.909	-0.693	0.910	2.654

Table 2. 2 Correlation Matrix

The table reports Pearson correlation coefficients between the unified CSR cost factor (IMR), social factor (IMR_S), and environmental factor (IMR_E), and other risk factors which have explanatory power on stock returns. The p-values are reported in parentheses, and ***, **, and * denotes significance at the 1%, 5%, and 10% levels, respectively.

Correlation Matrix									
	IMR	IMR_S	IMR_E	MKT	SMB	HML	UMD	RMW	CMA
IMR_S	0.819***								
	<.0001								
IMR_E	0.280***	0.076							
	0.000	0.301							
MKT	0.054	0.016	-0.089						
	0.469	0.827	0.230						
SMB	0.121	0.101	0.007	0.415***					
	0.102	0.170	0.922	<.0001					
HML	0.015	0.045	-0.097	0.220**	0.248***				
	0.836	0.540	0.190	0.003	0.001				
UMD	0.172**	0.132*	0.108	-0.342***	-0.182**	-0.425***			
	0.020	0.074	0.144	<.0001	0.013	<.0001			
RMW	-0.013	0.120	0.007	-0.407***	-0.371***	-0.117	0.140*		
	0.862	0.105	0.923	<.0001	<.0001	0.114	0.057		
CMA	-0.160**	-0.044	-0.181**	-0.090	0.068	0.494***	-0.127*	0.033	
	0.030	0.556	0.014	0.223	0.357	<.0001	0.085	0.654	
LIQ	0.094	0.072	-0.004	0.189**	0.028	-0.036	0.085	-0.074	-0.007
	0.204	0.331	0.956	0.010	0.705	0.626	0.251	0.320	0.920

Table 2. 3 Univariate Portfolios of Stocks Sorted by the Unified CSR Cost Beta

For each month, we sort stocks into five quantile portfolios based on their unified CSR cost beta (β_{CSR}). The unified CSR cost betas are obtained by regressing excess returns of individual stocks on the unified CSR cost factor (IMR), controlling for FF5 risk factors. Panel A indicates the equal-weighted portfolio returns, and Panel B reports the value-weighted returns. Low portfolio contains stocks with the lowest β_{CSR} and High portfolio consists of stocks with the highest β_{CSR}. The first three columns report the average size, book-to-market ratio, and the CSR cost beta of individual stocks across five quantile portfolios. Column 4 presents the average portfolio return, and columns 5-9 report the risk-adjusted returns (alphas), controlling for several risk factors: market, size, value, momentum, profitability, investment, and liquidity factors. The last row (High-Low) shows the average return and risk-adjusted return differences between High portfolio and Low portfolio. The t -statistics adjusted by Newey and West (1987) are presented in parentheses. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Equal-Weighted Return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IMR Beta Portfolios	Size	BM	Beta	Avg Ret	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	7.18	0.48	-1.59	1.60	0.13	0.39	0.40	0.35	0.36
				(4.26)	(0.76)	(3.80)	(3.82)	(3.82)	(3.73)
2	7.86	0.44	-0.55	1.47	0.14	0.30	0.29	0.22	0.22
				(4.56)	(1.22)	(3.48)	(3.43)	(2.71)	(2.73)
3	7.85	0.47	-0.04	1.39	0.03	0.22	0.23	0.17	0.18
				(4.08)	(0.29)	(3.23)	(3.50)	(2.69)	(2.99)
4	7.59	0.49	0.53	1.31	-0.13	0.11	0.14	0.08	0.10
				(3.62)	(-0.86)	(1.27)	(1.53)	(0.96)	(1.13)
High	7.39	0.61	1.82	1.19	-0.48	-0.17	-0.11	-0.21	-0.16
				(2.48)	(-2.05)	(-0.97)	(-0.66)	(-1.28)	(-0.99)
High-Low				-0.41*	-0.60**	-0.56**	-0.51**	-0.56**	-0.52**
				(-1.77)	(-2.53)	(-2.40)	(-2.18)	(-2.56)	(-2.32)

Panel B: Value-Weighted Return

IMR Beta Portfolios	Size	BM	Beta	Avg Ret	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	10.90	0.30	-1.33	1.54	0.28	0.24	0.24	0.25	0.26
				(4.88)	(1.48)	(1.28)	(1.21)	(1.35)	(1.33)
2	11.16	0.29	-0.55	1.41	0.38	0.31	0.29	0.18	0.17
				(5.54)	(2.81)	(2.43)	(2.28)	(1.72)	(1.65)
3	10.78	0.33	-0.05	1.20	0.07	-0.01	0.00	-0.10	-0.10
				(4.37)	(0.55)	(-0.09)	(0.02)	(-1.10)	(-1.12)
4	10.23	0.35	0.51	1.04	-0.20	-0.16	-0.14	-0.18	-0.18
				(3.42)	(-2.06)	(-1.66)	(-1.45)	(-2.12)	(-2.02)
High	10.26	0.48	1.77	0.90	-0.52	-0.42	-0.37	-0.42	-0.39
				(2.10)	(-2.07)	(-1.76)	(-1.59)	(-1.76)	(-1.64)
High-Low				-0.64*	-0.80**	-0.66**	-0.61*	-0.67**	-0.65*
				(-1.94)	(-2.28)	(-2.00)	(-1.82)	(-2.06)	(-1.94)

Table 2. 4 Portfolios Sorted by Unified CSR Cost Beta, Controlling for Firm Characteristics

For each month, we form equal-weighted quantile portfolios based on the unified CSR cost beta (β_{CSR}), controlling for other characteristics including size (Panel A), BM (Panel B), momentum (Panel C), and illiquidity (Panel D). CSR cost betas are obtained by regressing the excess return of individual stocks on the Fama-French 5 factors with the additional CSR cost factor (IMR). We first sort stocks into five quintile portfolios based on one of the firm characteristics. Within each firm characteristic quintile, we further form five portfolios by sorting stocks based on their CSR cost beta. All portfolios are balanced monthly. We then calculate the average return across five firm characteristic quantiles for each of five CSR cost beta portfolios. Low portfolio includes stocks with the lowest β_{CSR} and High portfolio contains stocks with the highest β_{CSR}. Column one presents the average return for equal-weighted portfolios, and the next five columns report the risk-adjusted returns (alphas) for equal-weighted portfolios, controlling for several risk factors: market, size, value, momentum, investment, profitability, and liquidity factors. The last row (High-Low) summarizes the average return and factor-adjusted return differences between High portfolio and Low portfolio. Newey-West (1987) adjusted t-statistics are displayed in parentheses, and ***, **, and * indicate the statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Controlling for Size

	(1)	(2)	(3)	(4)	(5)	(6)
IMR Beta Portfolios	Ret	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	1.63	0.19	0.40	0.41	0.37	0.37
	(4.55)	(1.20)	(4.00)	(4.03)	(4.00)	(3.98)
2	1.47	0.12	0.30	0.30	0.24	0.24
	(4.48)	(1.03)	(3.73)	(3.64)	(3.13)	(3.05)
3	1.39	0.01	0.21	0.23	0.17	0.18
	(3.96)	(0.11)	(3.28)	(3.59)	(2.51)	(2.71)
4	1.29	-0.14	0.10	0.13	0.06	0.08
	(3.59)	(-0.96)	(1.00)	(1.33)	(0.68)	(0.93)
High	1.17	-0.49	-0.19	-0.13	-0.21	-0.16
	(2.44)	(-2.07)	(-1.07)	(-0.78)	(-1.32)	(-1.01)
High-Low	-0.46*	-0.68***	-0.59**	-0.54**	-0.58**	-0.54**
	(-1.89)	(-2.73)	(-2.46)	(-2.28)	(-2.61)	(-2.40)

Panel B: Controlling for BM

IMR Beta Portfolios	Ret	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	1.60	0.14	0.39	0.41	0.36	0.37
	(4.37)	(0.91)	(4.20)	(4.20)	(4.12)	(4.02)
2	1.36	-0.01	0.17	0.17	0.10	0.11
	(4.01)	(-0.11)	(2.16)	(2.16)	(1.34)	(1.41)
3	1.36	0.01	0.20	0.22	0.15	0.16
	(3.94)	(0.06)	(2.40)	(2.64)	(1.89)	(2.12)
4	1.29	-0.16	0.06	0.10	0.04	0.06
	(3.53)	(-1.17)	(0.81)	(1.24)	(0.46)	(0.75)
High	1.35	-0.28	0.00	0.04	-0.02	0.01
	(2.96)	(-1.31)	(0.00)	(0.29)	(-0.16)	(0.06)
High-Low	-0.25	-0.42**	-0.39*	-0.36*	-0.39**	-0.36*

	(-1.20)	(-2.08)	(-1.95)	(-1.76)	(-2.03)	(-1.83)

Panel C: Controlling for Momentum

IMR Beta Portfolios	Ret	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	1.58	0.13	0.39	0.41	0.36	0.38
	(4.22)	(0.75)	(3.84)	(3.90)	(3.77)	(3.75)
2	1.46	0.11	0.27	0.28	0.21	0.21
	(4.40)	(0.97)	(3.13)	(3.21)	(2.62)	(2.68)
3	1.41	0.03	0.21	0.23	0.15	0.17
	(4.08)	(0.26)	(2.74)	(2.93)	(2.25)	(2.48)
4	1.32	-0.13	0.11	0.14	0.07	0.09
	(3.65)	(-0.85)	(1.41)	(1.81)	(0.95)	(1.19)
High	1.16	-0.46	-0.18	-0.14	-0.20	-0.16
	(2.53)	(-2.15)	(-1.15)	(-0.90)	(-1.36)	(-1.12)
High-Low	-0.42*	-0.59***	-0.57**	-0.54**	-0.56***	-0.54**
	(-1.94)	(-2.68)	(-2.61)	(-2.43)	(-2.73)	(-2.55)

Panel D: Controlling for Illiquidity

IMR Beta Portfolios	Ret	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	1.61	0.16	0.38	0.39	0.34	0.34
	(4.49)	(1.05)	(3.69)	(3.71)	(3.52)	(3.49)
2	1.47	0.13	0.31	0.31	0.25	0.25
	(4.54)	(1.10)	(3.84)	(3.76)	(3.49)	(3.45)
3	1.39	0.02	0.21	0.23	0.17	0.18
	(3.93)	(0.13)	(3.37)	(3.58)	(2.62)	(2.76)
4	1.32	-0.11	0.13	0.16	0.10	0.11
	(3.64)	(-0.73)	(1.47)	(1.75)	(1.17)	(1.37)
High	1.17	-0.50	-0.20	-0.14	-0.24	-0.18
	(2.44)	(-2.20)	(-1.20)	(-0.91)	(-1.49)	(-1.19)
High-Low	-0.44*	-0.66***	-0.58**	-0.53**	-0.57**	-0.53**
	(-1.81)	(-2.72)	(-2.44)	(-2.26)	(-2.57)	(-2.35)

Table 2. 5. Pricing of the Unified CSR Cost Factor

This table shows the estimated results for the second-stage of Fama-MacBeth regressions; the coefficient estimates of factors are based on 25 portfolios sorted on market beta (β_{MKT}) and the unified CSR cost beta (β_{CSR}). IMR is the unified CSR cost factor, MKT is the excess return on the market portfolio, SMB is size factor, HML is value factor, UMD represents the momentum factor, RMW is profitability factor, CMA is investment factor, and LIQ is the aggregate liquidity measure. Newey-West adjusted t-statistics are presented in parentheses. Symbols ***, **, and * indicate the statistical significance at the 1%, 5%, and 10% levels, respectively.

	CAPM+IMR	FF3+IMR	Carhart4+IMR	FF5+IMR	FF5+M+L+IMR
Constant	0.635**	0.480	0.466	0.877**	0.822*
	(1.98)	(1.19)	(1.14)	(2.05)	(1.90)
IMR	-0.512**	-0.488**	-0.485**	-0.371*	-0.384*
	(-2.41)	(-2.25)	(-2.23)	(-1.67)	(-1.72)
MKT	0.583	0.742	0.764	0.358	0.413
	(1.25)	(1.40)	(1.43)	(0.66)	(0.76)
SMB		-0.112	-0.012	-0.085	0.194
		(-0.27)	(-0.03)	(-0.22)	(0.46)
HML		-0.187	-0.110	0.023	0.179
		(-0.34)	(-0.20)	(0.04)	(0.32)
UMD			0.163		0.497
			(0.24)		(0.70)
RMW				0.432	0.461
				(1.43)	(1.52)
CMA				-0.349	-0.243
				(-1.24)	(-0.85)
LIQ					-0.416
					(-0.48)
Adj R^2	0.286	0.308	0.304	0.338	0.355

Table 2. 6 Robustness: Alternative Unified CSR Cost Beta

For each month, we sort stocks into five quantile portfolios based on the unified CSR cost beta (β_{CSR}). The unified CSR cost betas are obtained by regressing the excess return of individual stocks on the unified CSR cost factor (IMR), controlling for FF5 risk factors, momentum, and the liquidity factor. Panel A reports the equal-weighted portfolio returns and panel B reports the value-weighted returns. Low portfolio contains stocks with the lowest β_{CSR} and High portfolio contains stocks with the highest β_{CSR}. Columns 1-5 present the risk-adjusted returns (alphas), controlling for several well-known risk factors: market, size, value, momentum, profitability, investment, and liquidity factors. The last row (High-Low) illustrates the risk-adjusted return differences between High portfolio and Low portfolio. The t-statistics adjusted by Newey and West (1987) are displayed in parentheses. ***, **, and * indicate the statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Equal-Weighted Return					
	(1)	(2)	(3)	(4)	(5)
IMR Beta Portfolios	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	0.08	0.33	0.34	0.29	0.30
	(0.48)	(3.09)	(3.15)	(3.03)	(3.00)
2	0.17	0.34	0.34	0.28	0.28
	(1.43)	(3.76)	(3.69)	(3.15)	(3.14)
3	0.05	0.23	0.24	0.17	0.18
	(0.41)	(3.07)	(3.29)	(2.78)	(3.02)
4	-0.09	0.15	0.18	0.11	0.13
	(-0.64)	(1.83)	(2.17)	(1.43)	(1.77)
High	-0.51	-0.19	-0.13	-0.23	-0.18
	(-2.14)	(-1.11)	(-0.83)	(-1.43)	(-1.16)
High-Low	-0.59**	-0.53**	-0.48**	-0.52**	-0.48**
	(-2.46)	(-2.27)	(-2.08)	(-2.43)	(-2.23)

Panel B: Value-Weighted Return					
IMR Beta Portfolios	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	0.25	0.18	0.18	0.18	0.19
	(1.45)	(1.05)	(1.00)	(1.07)	(1.12)
2	0.36	0.30	0.28	0.19	0.18
	(3.22)	(2.88)	(2.69)	(2.21)	(2.10)
3	0.10	0.04	0.06	-0.06	-0.05
	(0.81)	(0.39)	(0.52)	(-0.55)	(-0.54)
4	-0.23	-0.19	-0.17	-0.21	-0.20
	(-2.26)	(-1.95)	(-1.65)	(-2.25)	(-2.06)
High	-0.48	-0.38	-0.33	-0.36	-0.33
	(-1.91)	(-1.60)	(-1.41)	(-1.55)	(-1.43)
High-Low	-0.73**	-0.56*	-0.51	-0.54*	-0.53*
	(-2.14)	(-1.77)	(-1.59)	(-1.80)	(-1.71)

Table 2. 7 Univariate Portfolios of Stocks Sorted by the Social Cost Beta

For each month, we form five quantile portfolios based on the social cost beta (β_{social}). The social cost betas are obtained by regressing the excess return of individual stocks on the social cost factor (IMR_S), controlling for FF5 risk factors. Panel A shows the equal-weighted portfolio returns and Panel B reports the value-weighted returns. Low portfolio contains stocks with the lowest β_{Social} and High portfolio contains stocks with the highest β_{Social}. The first three columns report the average size, book-to-market ratio, and the social cost beta of individual stocks across five quantile portfolios. Column 4 shows the average portfolio return, and the columns 5-9 report the risk-adjusted returns (alphas), controlling for commonly used risk factors: market, size, value, momentum, profitability, investment, and liquidity factors. The last row (High-Low) illustrates the differences of the average return and risk-adjusted return between High portfolio and Low portfolio. The t -statistics corrected by Newey and West (1987) are illustrated in parentheses. ***, **, and * indicate the statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Equal-Weighted Return									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IMR_S Beta Portfolios	Size	BM	Beta	Avg Ret	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	7.22	0.48	-2.01	1.61	0.15	0.42	0.42	0.34	0.35
				(4.37)	(0.88)	(3.93)	(3.92)	(3.63)	(3.61)
2	7.79	0.47	-0.62	1.41	0.08	0.27	0.28	0.24	0.24
				(4.13)	(0.54)	(3.12)	(3.11)	(3.12)	(3.17)
3	7.88	0.46	0.05	1.35	-0.03	0.17	0.18	0.12	0.12
				(3.98)	(-0.24)	(2.11)	(2.30)	(1.53)	(1.62)
4	7.59	0.48	0.74	1.32	-0.11	0.11	0.13	0.05	0.07
				(3.71)	(-0.80)	(1.14)	(1.43)	(0.55)	(0.71)
High	7.37	0.60	2.32	1.26	-0.40	-0.11	-0.05	-0.13	-0.08
				(2.68)	(-1.78)	(-0.62)	(-0.32)	(-0.81)	(-0.52)
High-Low				-0.34	-0.55**	-0.53**	-0.48**	-0.48**	-0.43*
				(-1.54)	(-2.26)	(-2.26)	(-2.06)	(-2.16)	(-1.96)

Panel B: Value-Weighted Return									
IMR_S Beta Portfolios	Size	BM	Beta	Avg Ret	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	11.29	0.28	-1.64	1.68	0.42	0.30	0.29	0.29	0.27
				(5.03)	(2.07)	(1.57)	(1.43)	(1.53)	(1.39)
2	11.12	0.33	-0.63	1.18	0.12	0.08	0.08	-0.04	-0.02
				(4.55)	(0.84)	(0.55)	(0.60)	(-0.36)	(-0.21)
3	10.61	0.31	0.04	1.20	0.06	0.03	0.04	-0.05	-0.05
				(4.51)	(0.68)	(0.39)	(0.50)	(-0.60)	(-0.68)
4	10.12	0.36	0.70	1.03	-0.26	-0.22	-0.20	-0.27	-0.26
				(3.20)	(-2.27)	(-1.99)	(-1.81)	(-2.56)	(-2.47)
High	10.15	0.46	2.17	0.98	-0.38	-0.32	-0.28	-0.31	-0.29
				(2.46)	(-1.76)	(-1.52)	(-1.38)	(-1.54)	(-1.40)
High-Low				-0.70**	-0.80**	-0.62**	-0.57*	-0.60**	-0.56*
				(-2.35)	(-2.42)	(-2.00)	(-1.82)	(-2.01)	(-1.83)

Table 2. 8 Univariate Portfolios of Stocks Sorted by the Environmental Cost Beta

For each month, we sort stocks into five quantile portfolios based on the environmental cost beta (β_{Env}). CSR cost betas are obtained by regressing the excess return of individual stocks on the environmental cost factor (IMR_E), controlling for FF5 risk factors. Panel A indicates the equal-weighted portfolio returns and Panel B reports the value-weighted returns. Low portfolio includes stocks with the lowest β_{Env} and High portfolio contains stocks with the highest β_{Env}. The first three columns report the average size, book-to-market ratio, and the environmental cost beta of individual stocks across five quantile portfolios. Column 4 describes the average portfolio return, and columns 5-9 report the risk-adjusted returns (alphas), controlling for the following risk factors: market, size, value, momentum, profitability, investment, and liquidity factors. The last row (High-Low) shows the average return and factor-adjusted return differences between High portfolio and Low portfolio. The adjusted t -statistics (Newey and West, 1987) are given in parentheses, and ***, **, and * denote the statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Equal-Weighted Return									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IMR_E Beta Portfolios	Size	BM	Beta	Avg Ret	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	7.34	0.50	-1.70	1.56	0.09	0.34	0.37	0.30	0.32
				(4.11)	(0.61)	(3.31)	(3.42)	(3.08)	(3.12)
2	7.84	0.46	-0.63	1.44	0.01	0.21	0.23	0.16	0.16
				(4.05)	(0.10)	(2.40)	(2.65)	(1.95)	(2.03)
3	7.86	0.47	-0.10	1.34	-0.05	0.13	0.13	0.08	0.08
				(3.90)	(-0.43)	(1.60)	(1.56)	(0.90)	(0.88)
4	7.63	0.49	0.46	1.43	0.04	0.25	0.26	0.20	0.20
				(4.12)	(0.30)	(3.33)	(3.34)	(2.94)	(2.89)
High	7.18	0.57	1.62	1.18	-0.39	-0.09	-0.02	-0.12	-0.06
				(2.70)	(-1.83)	(-0.68)	(-0.21)	(-0.96)	(-0.54)
High-Low				-0.38**	-0.49***	-0.43**	-0.40**	-0.42**	-0.38**
				(-2.29)	(-3.01)	(-2.58)	(-2.33)	(-2.43)	(-2.19)
Panel B: Value-Weighted Return									
IMR_E Beta Portfolios	Size	BM	Beta	Avg Ret	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	10.39	0.30	-1.49	1.49	0.16	0.14	0.16	0.18	0.18
				(4.62)	(1.03)	(0.92)	(1.02)	(1.23)	(1.23)
2	10.55	0.31	-0.61	1.14	0.01	-0.01	-0.02	-0.13	-0.14
				(3.97)	(0.08)	(-0.11)	(-0.14)	(-1.05)	(-1.13)
3	10.94	0.31	-0.10	1.29	0.17	0.11	0.11	0.04	0.04
				(4.69)	(1.49)	(1.00)	(0.98)	(0.42)	(0.38)
4	11.04	0.37	0.45	1.24	0.11	0.06	0.04	-0.03	-0.03
				(4.39)	(0.93)	(0.58)	(0.39)	(-0.32)	(-0.35)
High	10.74	0.43	1.39	0.78	-0.60	-0.53	-0.48	-0.55	-0.50
				(2.08)	(-3.03)	(-2.76)	(-2.47)	(-2.84)	(-2.60)
High-Low				-0.70***	-0.76***	-0.68***	-0.63**	-0.73***	-0.68***
				(-2.94)	(-3.03)	(-2.67)	(-2.45)	(-2.94)	(-2.66)

Table 2. 9 Pricing of the Social and Environmental Cost Factors

This table shows the estimated results for the second-stage of Fama-MacBeth regressions; the coefficient estimates of factors are based on 25 portfolios sorted on market beta (β_{MKT}) and the social cost beta (β_{social}). MKT is the excess return on the market portfolio, IMR_S is the social cost factor, IMR_E is the environmental cost factor, SMB is size factor, HML is value factor, UMD is the momentum factor, CMA is investment factor, RMW is profitability factor, and LIQ is the aggregate liquidity factor. Newey-West adjusted t-statistics are presented in parentheses. ***, **, and * indicate the statistical significance at the 1%, 5%, and 10% levels, respectively.

	CAPM+IMR	FF3+IMR	Carhart4+IMR	FF5+IMR	FF5+M+L +IMR
Constant	0.711**	0.610	0.601	1.284**	1.291**
	(2.13)	(1.46)	(1.29)	(2.20)	(2.15)
IMR_S	-0.322*	-0.320*	-0.339*	-0.074	-0.041
	(-1.83)	(-1.66)	(-1.67)	(-0.37)	(-0.21)
IMR_E	-0.392**	-0.396**	-0.396**	-0.464**	-0.481**
	(-2.17)	(-2.37)	(-2.17)	(-2.49)	(-2.52)
MKT	0.485	0.593	0.599	-0.079	-0.082
	(1.02)	(1.16)	(1.03)	(-0.12)	(-0.12)
SMB		-0.202	-0.337	0.006	0.029
		(-0.55)	(-0.75)	(0.01)	(0.07)
HML		0.181	0.216	0.178	0.185
		(0.39)	(0.43)	(0.36)	(0.37)
UMD			-0.714		-0.309
			(-0.95)		(-0.40)
RMW				0.399	0.364
				(1.15)	(0.93)
CMA				-0.457	-0.467
				(-1.48)	(-1.53)
LIQ					0.305
					(0.26)
Adj R^2	0.274	0.322	0.320	0.349	0.355

Table 2. 10 Robustness: Univariate Portfolios of Stocks Sorted by Social Cost Beta and Environmental Cost Beta

Panel A shows the univariate portfolio analysis based on the sorting on social cost beta. The social factor is constructed from the MSCI ESG dataset, and the environmental factor is constructed from the Refinitiv ESG dataset. For each month, we sort stocks into five quantile portfolios by sorting stocks based on their social cost beta (β_{social}). The social cost betas are obtained by regressing the excess return of individual stocks on the social cost factor (IMR_S), controlling for FF5 risk factors. Panel B reports the univariate portfolio analysis based on the sorting on environmental cost beta. Five quantile portfolios are formed based on the environmental cost beta (β_{Env}). Low portfolio consists of stocks with the lowest beta and High portfolio consists of stocks with the highest betas. The first three columns report the average size, book-to-market ratio, and the social cost beta (environmental cost beta in Panel B) of individual stocks across fivequantile portfolios. Column four details the average portfolio return, and the next five columns report the risk-adjusted returns (alphas), controlling for several well-known risk factors: market, size, value, momentum, profitability, investment, and liquidity factors. The last row (High-Low) shows the average return and risk-adjusted return differences between High portfolio and Low portfolio. The adjusted t -statistics (Newey and West, 1987) are presented in parentheses. Symbols ***, **, and * indicate the statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: Social Cost Beta Portfolio

IMR_S Beta Portfolios	Size	BM	Beta	Avg Ret	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	7.21	0.49	-1.53	1.65	0.19	0.46	0.47	0.40	0.41
				(4.41)	(1.06)	(4.86)	(4.89)	(4.45)	(4.38)
2	7.81	0.46	-0.49	1.35	-0.02	0.16	0.18	0.10	0.11
				(3.96)	(-0.14)	(1.52)	(1.61)	(1.00)	(1.08)
3	7.85	0.47	0.02	1.39	-0.00	0.19	0.21	0.14	0.15
				(4.05)	(-0.03)	(2.53)	(2.80)	(1.89)	(2.13)
4	7.64	0.48	0.56	1.38	-0.04	0.20	0.22	0.16	0.18
				(3.82)	(-0.26)	(2.19)	(2.45)	(1.84)	(2.01)
High	7.36	0.58	1.78	1.18	-0.44	-0.16	-0.11	-0.18	-0.15
				(2.58)	(-1.99)	(-0.91)	(-0.69)	(-1.13)	(-0.90)
High-Low				-0.46**	-0.63***	-0.62***	-0.59**	-0.59***	-0.56**
				(-2.18)	(-2.67)	(-2.75)	(-2.61)	(-2.73)	(-2.54)

Panel B: Environmental Cost Beta Portfolio

IMR_E Beta Portfolios	Size	BM	Beta	Avg Ret	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	7.12	0.52	-1.31	1.55	0.02	0.30	0.30	0.26	0.25
				(4.00)	(0.16)	(3.23)	(3.25)	(2.83)	(2.68)
2	7.70	0.49	-0.47	1.42	0.00	0.22	0.24	0.17	0.18
				(4.04)	(0.00)	(2.17)	(2.45)	(1.82)	(1.98)
3	7.89	0.47	-0.05	1.41	0.03	0.24	0.25	0.17	0.19
				(4.12)	(0.27)	(2.94)	(3.22)	(2.45)	(2.75)
4	7.78	0.47	0.36	1.30	-0.05	0.16	0.17	0.11	0.13
				(3.62)	(-0.35)	(1.97)	(2.21)	(1.45)	(1.84)
High	7.37	0.53	1.23	1.28	-0.31	-0.05	-0.01	-0.09	-0.05
				(3.05)	(-1.74)	(-0.50)	(-0.07)	(-0.99)	(-0.54)
High-Low				-0.27**	-0.34***	-0.34***	-0.31**	-0.35**	-0.31**
				(-2.25)	(-2.76)	(-2.65)	(-2.29)	(-2.54)	(-2.15)

3. Investment Decisions and Investor Morality: A Behavioral Approach

3.1 Introduction

Many investors pursue not only financial goals but also aim to achieve some social responsibility objectives (Beal et al. 2005; Williams 2007; Renneboog, Horst and Zhang 2008). In recent years, the "moral investment" sector has grown rapidly in the U.K. fund management industry (Mackenzie and Lewis 1999), and investment in sustainable, responsible, and impact assets has risen in the U.S. from $6.57 trillion to $17.1 trillion during 2014-2020. Socially responsible investment (SRI) constitutes one-third of assets under professional management. (U.S. Social Investment Forum, 2020). According to a 2019 Morgan Stanley survey, 85% of investors consider investing in a socially responsible assets, and 42% of them already hold an SRI. Investors concerned about social and environmental issues pursue socially responsible investments and shun unethical investments. For example, Luo and Balvers (2017) found that corporate social responsibility (CSR)-violating firms have a higher exposure to boycott risk. Also, a certain number of investors are less likely to hold "sin" stocks (stocks of companies that are involved in gambling, tobacco, and alcohol business) (Hong and Kacperczyk, 2009).

Previous research, which has focused on firm-level CSR, has studied the link between CSR and financial performance (e.g., Hamilton, Jo, and Statman 1993; Guerard, 1997; Statman, 2000; Brammer, Brooks and Pavelin, 2006; Edmans, 2011). Another strand of the literature examines the impact of CSR on financial risk (e.g., Fabozzi, Ma, and Oliphant, 2008; Lee and Faff, 2009; Albuquerque, Durnev, and Koskinsen, 2013; Luo and Balvers, 2017). However, relatively few papers investigate the influence of individuals' ethical views as they make financial decisions. That raises the question of what human characteristics affect individuals' decision-making with respect to CSR. What factors or conditions would trigger or change an individual's decisions when considering whether to invest in a CSR-violating company? In this chapter, we fill this research gap by connecting the human characteristic of moral identity with ethical decision-making in the financial investment domain. In addition, we study how financial incentives and the physical distance between investors and immoral companies affects their decisions.

Moral identity, an individual-difference variable, represents a social identity incorporating an individual's morality level in a cognitive schema. It measures the self-conception associated with moral characters, and, and it is consistently associated with individuals' moral actions (Aquino and Reed, 2002). Moral identity has been shown to predict moral decision-making in a prosocial perspective (e.g., Aquino and Reed, 2002; Shao, Aquino, and Freeman, 2008; Winterich et al., 2013). According to Aquino and Reed (2002), people high in moral identity value themselves as moral persons, and their behaviors are consistent with their self-value and social identity, and they feel more obligated to make ethical decisions. The decisions of low moral identity individuals are quite different. For example, recognition incentive increases the donation participation for people with low moral identity (Winterich et al. 2013). It is therefore important to study the extent to which the investment decisions of individuals with high moral identity differ from those of individuals with low moral identity.

To address these issues, we conduct three studies. In Study 1, we use firms in the pornography industry as a proxy for "immoral" stocks; the result confirms that individuals with lower moral identity are more likely to invest in immoral portfolios which promise a higher financial incentive. In contrast, individuals with a high moral identity are more likely to sacrifice the higher return and shun immoral stocks. The assumption that immoral firms provide higher financial returns is supported by the literature (e.g., Hong and Kacperczyk, 2009; Hsu, Li and Tsou, 2020; Bolton and Kacperczyk, 2020).

While individuals with a low moral identity may have a preference for immoral stocks, it is not clear whether these individuals are actually unethical or whether they are simply being driven by the promised financial benefits. It is necessary to determine whether individuals with lower moral identity would make the same investment decisions when the immoral stocks are not incentivized by higher returns. Therefore, we further discover how financial return moderates the relation between moral identity and unethical decision making. In study 2, we use firms in the firearms industry as a proxy for immoral stocks; our results again confirm that individuals with lower moral identity are more likely to invest in immoral stocks only when they yield a higher return.

Study 3 is based on the notion that a firm's location and the physical distance between investors and firms plays a role in financial decisions. The home bias phenomenon suggests that fund managers and individual investors have a preference in domestic equity holdings, suggesting that the physical location of the company is significantly linked to investors' investment decisions (Coval and Moskowitz 1999; Seasholes and Zhu 2010; Pool, Stoffman and Yonker, 2015). We therefore study the moderating effect of physical distance between investors and the location of the company they are investing in. We conduct a between-subjects experimental study and use firms with toxic emissions as a proxy for immoral stocks. We then study the effects of two moderators (financial return and physical distance) on the relation between moral identity and unethical investing. Results show a significant three-way interaction, which suggests that while immoral stocks provide a return incentive, individuals with low moral identity have a higher willingness to invest (WTI) only when they perceive themselves to be physically distant from the immoral company. The mechanism behind this relation is that distance proximity triggers a bias: the scope insensitivity phenomenon, which is defined as individuals are less sensitive to the magnitude or scope (e.g., size, portion) of the object that being evaluated (e.g., Fetherstonhaugh, Slovic, Johnson, & Friedrich, 1997; Hsee & Rottenstreich, 2004). This bias causes individuals to be less influenced by the return incentive when the perceived distance to the immoral company is small. Low moral identity individuals are not incentivized by the higher return, and the WTI in an immoral portfolio is low regardless the level of financial returns. For individuals with higher moral identity, return incentive does not increase their WTI in immoral stocks regardless of the perceived distance to the immoral company.

This chapter is related to several strands of literature. First, this chapter is relevant for the study of how individuals with different moral identities make decisions with ethical implications. It is also related to the literature that focuses on moderating and incentive variables which affect the relation between moral identity and ethical decisions (e.g., Aquino & Reed, 2002; Winterich et al. 2013). Our study of the moderating roles of physical distance in influencing financial investment decisions is relevant for the literature that studies the impact of physical distance in decision-making (e.g., Barnett, 2001; Mencl and May, 2009; Touré-Tillery and Fishbach, 2017; kogut,Ritov, Rubaltelli, and Liberman 2018; Chang and Pham, 2018). This chapter is closely related to Chang and Pham (2018), which disentangles the impact of physical distance on scope insensitivity in the consumer behavior domain. We extend Chang and Pham (2018) and demonstrate that distance proximity triggers the scope insensitivity phenomenon in an investment context.

This chapter provides both theoretical and practical insight into the ethical investment literature, and our conceptual model provides evidence of a three-way interaction among moral identity, financial return, and physical distance on unethical investment. We contribute to the literature by clarifying the link between human moral values and decisions that have an ethical component; this helps us to understand the role of moral identity in a financial investment context. In addition, we find that while higher financial returns strengthen the relation between moral identity and unethical investment, the physical location of the immoral company moderates this relation. Finally, our findings provide further evidence that the scope insensitivity phenomenon is more prevalent when physical distance is proximate, and we interpret the scope insensitivity phenomenon in the financial domain.

The remainder of this chapter is organized as follows: Section 2.2 examines the relevant literatures and presents our hypotheses. Section 2.3 describes our study design, data collection methods, and results. In Section 2.4, we discuss the limitation and implication of our findings.

3.2 Development of Hypotheses

We examine the impact of moral identity on unethical decision-making as it is moderated by financial incentives and the perceived physical distance between investors and the immoral company.

3.2.1 Moral Identity and Unethical Decision Making

A growing body of research suggests that investors are not always rational, and that their investment behaviors differ due to personal biases and psychological influences. Investors who are concerned about social or environmental issues consider not only financial returns, but also take into account issues like social responsibility or sustainability development when they are in the process of financial decision-making (Beal et al. 2005; Williams 2007; Renneboog, et al. 2008; Rubaltelli, Lotto and Rumiati, 2015).

Rubaltelli et al. (2015) conduct an experimental study examining the psychological motivation of moral investment. They find that when participants' motivations for investment are consistent with their moral values, they are more likely to choose a "moral" portfolio over an "immoral" one. Investors whose motivation is to be consistent with their moral values also feel less regret about their decision if they discover that an alternative portfolio earns more. Thus, both financial gain and social responsibility considerations impact investors' decision-making. Other research also documents a trade-off between moral value and financial returns in investment decisions. For example, pro-environment investors are willing to incur a potential loss to make an environment-friendly investment (Lewis et al. 1995; Baker, Bergstresser, Serafeim, and Wurgler, 2018; Bolton and Kacperczyk, 2020). These findings suggest that some investors gain utility not only from financial gain, but also from making ethical investments.

Morality is associated with moral cognition and behavior. Moral identity, developed by Aquino and Reed (2002), is based on the fundamental issues of self-concept and social identity. Their trait-based scale has been empirically shown to be reliable and valid in measuring morality. Moral identity is interpreted as a determinant of an individual's moral behavior and represents an individual's moral standard (e.g., Blasi, 1984; Lapsley and Lasky, 2001; Aquino and Reed, 2002; Aquino and Freeman, 2009; Shao et al. 2008). A large body of work links moral identity to ethical decision-making; specifically, people high in moral identity are more likely to engage in charitable behavior, including donations of food, time, and money (e.g., Aquino and Reed, 2002; Reed, Aquino and Levy, 2007).

We extend the concept of ethical decision making into financial investment and propose that moral identity has an impact on ethical investment. According to Aquino and Reed (2002), moral identity consists of two components: internalization and symbolization While internalization represents the private aspect of the moral standard, symbolization focuses on the "public" perspective. In this chapter, we examine how day traders or fund managers invest clients' money. Since the portfolio information in terms of asset allocation is public for their clients, we focus on the "public" aspect of morality identity. Therefore, the moral identity in this chpter refers to symbolic moral identity. While people with high moral identity are more likely to engage in prosocial behavior, we propose that they are also more likely to boycott unethical investments to maintain their public moral reputation. Thus, they have a lower WTI for an immoral portfolio. In contrast, individuals who have low moral identity are more likely to be incentivized by a higher return, therefore, they have a higher WTI in unethical investments.

Hypothesis 1: In general, there is a negative relation between moral identity and WTI in immoral stocks.

3.2.2 The Incentive of Financial Returns

Previous research shows that unethical investment is associated with a higher financial return incentivize. Pastor, Stambough, and Taylor (2020) theoretically propose that green firms have a lower expected return, and Baker et al. (2018) discover that green (environmentally responsible) bonds also earn a lower return. Hong and Kacperczyk (2009) present empirical evidence that "sin" stocks generate higher returns. While unethical investment is associated with a higher financial return, how would investors with different levels of moral identity respond to this incentive? According to the literature, moral investors (who are concerned about social and environmental issues) are willing to sacrifice part of their returns to invest in socially responsible stocks (e.g., Renneboog, et al. 2008 and Barber, Morse, and Yasuda, 2020). However, some investors engage in SRI only when socially responsible activities are coupled with an economic benefit (Petersen and Vredenburg, 2009). Some investors consider financial returns more important than social issues, and they try to exclusively maximize their wealth and do not care about CSR

(Nilsson, 2009). For example, Larcker and Watts (2020) find that many investors are not willing to forgo financial benefits to invest in pro-social or pro-environmental assets. While individuals with low moral identity are more likely to invest in immoral portfolios, are they only incentivized by higher returns and wealth maximization? How would people with a lower moral identity respond to immoral portfolios when the returns on the immoral portfolios are no different from other stocks?

Winterich et al. (2013) find that people with low moral identity are more likely to take part in charity behaviors when they receive recognition for their participation (recognition acts as a reinforcement for charitable behavior). When ethical decisions provide the incentive of recognition, they induce people with low moral identity to engage in prosocial activities. This evidence suggests that people with lower moral identity are not entirely unethical, and their actions could be driven by excessive benefits (e.g., recognition or financial incentive) Therefore, we speculate that higher financial returns incentivize investors with lower moral identity to invest in unethical stocks. However, when an immoral portfolio does not provide a higher return, people with lower moral identity may have a lower WTI for unethical portfolios. People with high moral identity are not affected by financial incentives. They behave consistently with their morality standard, and they care about their public image. Thus, they shun unethical investments regardless of the incentive of greater financial returns. Therefore, their WTI in immoral portfolio is low regardless of the level of financial returns.

> Hypothesis 2: Higher financial returns incentivize participants with a low moral identity to invest in immoral portfolios, while individuals with a high moral identity are less likely to invest in immoral portfolios regardless of the presence or absence of a financial incentive.

3.2.3 The Effect of Physical Distance (Physical Proximity)

The impact of distance on decision-making has been investigated in recent studies. Touré-Tillery and Fishbach (2017) apply secondary archival data to study distance proximity and prosocial behavior. They find that the amount of donations is negatively associated with the distance between the donor and the recipient. For example, alumni donate more money when their residence is closer to their alma mater. Kogut et al. (2018) show that the perceived distance between donors and victims of a humanitarian crisis (e.g., earthquake and fatal illness) affects donors' willingness to give. Specifically, increased distance decreases the willingness to donate when the victims are unidentified.

The affective system of decision-making documents that individuals' judgement and decisions are determined by their affective feeling. Proximity plays a role in affective decision-making. For example, Chang and Pham (2013) discover that the affective feelings amplify with respect to temporal proximity, and Chang and Pham (2018) find that physical proximity dominates affective superiority. Specifically, the self-oriented system (immediate self) suggests that when individuals make decisions, their judgments are most dependent on what is happening "here and now." In addition, the distance between the target object and immediate self influences individuals' preference and action and further triggers a judgement bias, so-called scope insensitivity phenomenon, interpreted as individuals have a lower sensitivity to numerical quantities for the target objects. Chang and Pham (2018) conduct several studies and find that participants have a significantly higher willingness to pay (WTP) for four sessions of a DVD collection of popular TV shows compared to one session of DVDs when they buy the DVDs from a friend living 500 miles away. However, the maximum WTPs for two sets of DVD collection (four sessions vs one session) are not significantly difference when individuals buy DVDs from a friend living close by. This finding suggests that individuals are less sensitive to monetary values when they are close to the objects that are being evaluated. Therefore, Chang and Pham conclude that the judgement bias of scope insensitivity is more pronounced in terms of proximity.

In terms of unethical investments, while individuals with lower moral identity are incentivized by the higher returns of immoral assets (and thus have a higher WTI), it is important to determine if their judgment about the return level of unethical investing will be further affected by their distance from the immoral firms. The decision whether to invest in immoral portfolios could be different when investors feel distant or close to the location of the immoral firms. Since Change and Pham (2018) find that the physical proximity amplifies individuals' scope insensitivity in decision-making, we conjecture that investor could be insensitive to the return level of an investment when they perceive that they are close to the immoral firm. In other words, individuals are only sensitive to a higher level of financial returns earned by immoral portfolios while they are distant from those immoral firms. Thus, people with low moral identity are more motivated by the higher return level of immoral stocks, and have a higher WTI in an immoral portfolio. In contrast, when individuals are close to immoral firms, the distance proximity triggers the judgement bias of scope insensitivity, and they may not perceive the higher level of return incentives earned by immoral firms, hence they are less motivated to invest in immoral portfolio even through the portfolios is associated with a higher return. To study the moderating role of physical distance among the moderating effect of financial return on the relation of moral identity and unethical investment, the hypothesis is developed as follows.

> Hypothesis 3: There is a three-way interaction among moral identity, financial return, and physical proximity in ethical investment decision-making.
>
> Hypothesis 3a: When participants perceive that they are distant from the immoral company, there will be a two-way interaction between moral identity and financial returns: a higher return will induce the individuals with low moral identity to invest in immoral portfolio, thus their WTI in immoral portfolio is higher when the return incentive is higher.
>
> Hypothesis 3b: When participants perceive that they are close to the immoral company, the two-way interaction of moral identity and financial return does not occur: higher return will not motivate individuals with low moral identity since the distance proximity trigger the scope insensitivity, therefore, their WTI in immoral portfolios does not increase with the higher level of financial incentive.

3.3 Experimental Studies

3.3.1 Study 1

To test Hypothesis 1, we conducted a laboratory experiment to examine the relation between moral identity and unethical decision making. All participants were asked to choose between two investment portfolios: an immoral portfolio or a neutral portfolio.

Unethical investing was manipulated in this study. We used the portfolio which includes companies in the pornography industry as a proxy for an immoral investment, and the portfolio which includes companies in the airline industry as a proxy for a neutral portfolio (see Appendix 2.2 for details). Following the portfolio choices, we measured participants' moral identity. To assess the demographic-based effects, we collected participants' demographic information at the end of the experiment. Column 1 in Table 3.1 display the summary statistics for our sample data in Study 1.

3.3.1.1 Method

We recruited 83 students from the Corporation Finance class (FIN 2200) in the Asper school of Business at the University of Manitoba (female = 46%, mean age = 22, SD = 1.96). Participants received credit toward their course grade for their participation. The immoral portfolio provided a 10% expected return, while the neutral portfolio had a 6% expected return; this is consistent with the finance literature, which suggests that immoral stocks earn higher financial returns than conventional securities (Hong and Kacperczyk, 2009; Bolton and Kacperczyk, 2020).

To measure individuals' moral identity, we used a well-established 10-item moral identity scale[2] (Aquino and Reed, 2002). Participants were asked to visualize a person with the following characteristics: "caring, compassionate, fair, friendly, generous, helpful, hardworking, honest, and kind." Participants then rated 10 items on a 7-point Likert scale (1 = Strongly disagree and 7 = Strongly agree). Five statements were used to measure internalized moral identity and five items were used to measure symbolic moral identity. While "internalized moral identity directly taps into the self-importance of the moral characteristics, symbolic moral identity taps a more general sensitivity to the moral self as a social object whose actions in the world can convey that one has these characteristics" (Aquino and Reed, 2002, p1436). In other words, internalized and symbolic moral identity represent the private and public aspects of moral characteristics. In this study, we study decision-making of traders and portfolio managers, who invest on behalf of their clients. therefore, we are only interested in symbolic moral identity. An illustrative item representing symbolic moral identity was "It would make me feel good to be a person who

[2] The moral identity measurement is described in the appendix.

has these characteristics." We averaged the score of the five symbolic statements to represent each individual's moral identity. Higher moral identity suggests that individuals concern about ethical issues publicly and they are more willing to enhance their public moral character. The summary statistics for moral identity (for all three studies) are reported in Table 3.1.

3.3.1.2 Results

To determine whether our manipulation of the unethical investment was successful, we first examined the participants' perceptions in terms of unethical investing. Participants were asked their perceived moral value of two industries (pornography vs. airlines) on a 7-point Likert scale (1 = very immoral and 7 = very moral). Participants perceived that the pornography industry (M = 3.23; SD = 1.61) was significantly less moral than the airline industry (M = 5.59; SD = 1.21; t statistics = 10.52; $p < 0.01$).

The logistic regression results for Study 1 are summarized in Column 1-2 of Table 3.2. Regressing the portfolio choice (dependent variable: investing in immoral portfolio = 1 and investing in neutral portfolio = 0) on moral identity yielded a coefficient of -0.515, with a standard error of 0.245. The estimate of the coefficient is statistically significant at the 5% level. This result suggests that moral identity is negatively associated with an unethical investment choice. Specifically, people with lower moral identity are more likely to choose an immoral portfolio. We also controlled for gender in the study, since women are more likely to make ethical decisions, and more willing to engage in charitable behavior (e.g., Gilligan, 1982; O'Fallon and Butterfield, 2005; Winterich et al. 2009). We coded the gender as a dummy variable (female = 1 and male = 0) to examine whether gender plays a role in our study. The coefficient estimate for the gender variable was -1.147 with a 5% significance level, confirming that women had a lower willingness to make unethical investments.

3.3.2 Study 2

To test Hypothesis 2, in this study we assessed the moderating role of financial return on the impact of moral identity on unethical decision making. Participants were presented with two portfolios (immoral vs. neutral), and then asked to make their investment choice. The return incentive and the unethical investment were manipulated. A portfolio that involved the firearms industry was used as a proxy for an immoral portfolio, and a portfolio which involved the construction industry was used as a proxy for the neutral portfolio (see Appendix 2.3 for details). In the study design, we asked respondents to choose between "immoral vs. neutral" portfolio instead of "immoral vs moral" to avoid using extremely sharp contrast. After participants made their portfolio choice, we measured their moral identity and gathered demographic information. The summary statistics for the data collected in Study 2 are reported in column 2 of Table .31.

3.3.2.2 Method

We used a 2 (moral identity: high vs. low) by 2 (financial return: high vs. low) between-subjects design, and 195 people participated in this study (female = 49%, mean age = 22, SD = 3.08). Participants were randomly assigned into one of the two return conditions. In the low return condition, both immoral portfolio and neutral portfolio had a 6% expected rate of return. In the high return condition, the immoral portfolio had an 8% expected return and the neutral portfolio has a 6% expected return.

3.3.2.3 Results

To confirm that we effectively manipulated unethical decision-making, we asked participants about their perceived moral value of the two industries (firearm vs construction) using a 7-point Likert scale (1 = very immoral and 7 = very moral). Respondents' morality perceptions of the firearms industry (M = 3.40; SD = 1.35) were significantly lower than for the construction industry (M = 5.54; SD = 1.14; t statistics = 16.19; $p < 0.01$).

We then conducted a logistic regression and regress the dependent variable of portfolio choice (firearm industry = 1 and construction industry = 0) on (1) moral identity, (2) the return incentive (high = 1 and low = 0), and (3) the interaction between moral identity and financial return. The regression results are listed in Column 3 of Table 3.2. The coefficient estimate for the interaction variable was -0.719 with a standard error of 0.398, suggesting that participants with a lower moral identity were more likely to choose the immoral portfolio when the financial incentive was high. Also, the coefficient estimate of the return variable was positive and significant at the 1% level, suggesting that higher returns incentivized individuals to invest in immoral stocks. We also controled for gender

(Column 4 of Table 3.2), and it did not have an impact on the significant two-way interaction of moral identity and return.

Figure 3.2 presents the relation between moral identity and unethical decision-making under two return conditions. There is a negative and significant relation between moral identity and unethical investing only in the high return condition. The significant negative relation disappears when the immoral portfolio is not associated with a higher return incentive. This result implies that low moral identity participants only have a higher willingness to hold immoral stocks when there is a financial inventive. In other words, low moral identity people are less immoral when there is no investment incentive.

3.3.3 Study 3

To test Hypothesis 3, we study the moderating role of physical distance on the relation among moral identity, financial return, and ethical decision-making. Participants were asked their WTI in a portfolio. Then respondents' moral identity and demographic information are measured following the portfolio choice question. In Study 3, the return incentive, participants' distance from the immoral company, and unethical investments are all manipulated. Toxic emissions are used as a proxy for immorality in this technology portfolio (see Appendix 2.4 for details). To manipulate participants' perceived distance from the immoral company, they were told that the factories which generated the toxic emission were located in the U.S. (Russia).

3.3.3.1 Method

We used a 2 (moral identity: high vs. low) by 2 (return: high vs. low) by 2 (distance: distant vs. close) between-subject design, which results in eight conditions. A total of 536 university students (female = 47%, mean age = 22, SD = 4.09) participated in this study and they completed the survey in our physical laboratory. Two conditions in terms of participants' moral identity were measured in the study. Participants were assigned randomly to one of the four conditions (distant and high return, distant and low return, close and high return, and close and low return). The moderated moderating model is shown in Figure 3.1, and the regression equation in our study in is shown as follows.

$$
\begin{aligned}
&Ethical\ Decision\ Making \\
&\quad = \alpha + \beta_1 MI + \beta_2 Return + \beta_3 Distance + \beta_4 MI * Return + \beta_5 MI \\
&\quad * Distance + \beta_6 Return * Distance + \beta_7 MI * Return * Distance + \varepsilon
\end{aligned}
$$

where MI represents individuals' moral identity, which was measured on a 7-point scale. Both return (1 = high return and 0 = low return) and distance (1 = distant and 0 = close) were categorical variables.

3.3.3.2 Pretests for Distance Manipulation

We pretested the distance manipulation before measuring the dependent variable of unethical decision-making. We recruited 135 participants to rate the physical distance (1 = close and 100 = distant) of a list of countries, including the United States, Japan, Canada, France, China, Italy, United Kingdom, Germany, Russia, India, Nigeria, South Korea. We then calculated the perceived distance of these countries and compare the means between groups. The result suggested that we use the United States (M = 43.63) as the proxy for the close condition, and Russia (M = 60.81) as the proxy for the distant condition.

3.3.3.3 Pretest for Unethical Investment Manipulation

Immoral behavior was also pretested before conducting the main study. We recruited 106 participants to pretest the morality rating of immoral behavior, such as alcohol, gambling, tobacco, pornography, nuclear energy, weapons production, genetically modified organisms, cannabis, child labor, violation of basic human rights, vivisection, toxic emissions, and waste. We asked participants to rate the moral rating for all of the above conditions (1 = slightly immoral and 100 = extremely immoral). We avoid using the choices which were perceived as very immoral perception in our study, such as violate basic human rights (M = 77.72) and child labor (M = 75.12). Also, we avoid using choices which were perceived as less immoral, such as genetically modified organisms (M = 32.44) and cannabis (M = 34.92). Thus, toxic emissions (M = 66.64) which was perceived as moderately immoral was used as the proxy for the immoral behavior in our study.

3.3.3.4 Results

3.3.3.4.1 Manipulation Check

We first examined the perception of expected return for the immoral portfolio. The manipulation check confirmed that participants perceived that the expected return in the high return condition (M = 4.62; SD = 1.25) was much higher than that in the low return condition (M = 4.23; SD = 1.22; t statistics = 3.47; $p < 0.01$). In addition, we tested participants' perceptions of physical distance from the factory involved in the toxic emissions. The manipulation check revealed that participants perceived that the U.S. (M = 40.81; SD = 18.44) was much closer than Russia (M = 68.79; SD = 19.43; t statistics = 15.88; $p < 0.01$).

3.3.3.4.2 Experimental Results

In the main test, we examine the moderating effects of financial return and physical distance on the link between moral identity and immoral portfolio choice. Table 3.2 reports the regression results. The regression analysis demonstrates that the three-way interaction among moral identity, financial return, and physical distance on participants' immoral investments is significant at the 10% level with a coefficient estimate of 0.582 and a standard error of 0.325. Recall that Study 2 find that respondents with a lower moral identity have a higher WTI in immoral portfolio only when the immoral portfolio is associated with a higher return. The estimated negative coefficient in Study 3 could be interpreted as follows: The participants with a lower moral identity are more likely to invest in an immoral portfolio only when the immoral portfolio has both a higher return incentive and the perceived distance from the immoral factory is large. The regression result suggests that physical distance further moderates the relation among moral identity, financial returns, and unethical investment. In other words, the physical distance triggers the scope insensitivity phenomenon in our study. Participants are less sensitive to financial returns when they perceive that they are close to the immoral factory, thus participants who are low in moral identity are not incentivized by the high returns. Therefore, participants are less likely to invest in an immoral portfolio with a higher return when they are closed to the immoral factory. The negative and significant three-way interaction among moral identity, financial return, and physical distance on participants' immoral investments is robust after we control for gender. To further clarify the moderating effects of financial return and distance, we also analyze the interaction of moral identity and financial return on unethical decision making in the distant condition (upper panel in Figure 3.3) and the close condition (lower panel in Figure 3.3). The link between moral identity and unethical decision-making is conditional on financial return and physical distance. In both conditions, participants high in moral identity are not affected by the financial returns, and the WTI in an immoral portfolio remains low. The upper panel in Figure 3.3 shows a significant two-way interaction ($\beta = -0.4525$, $p = 0.0494$) between moral identity and unethical investing for two return conditions. This result suggests that in the distant condition (factories are located in Russia), the participants with lower moral identity have a much higher WTI in an immoral portfolio while the financial return is high compared to the low return condition. In addition, this significant two-way interaction is driven by the negative relation between moral identity and unethical investing in the high return condition ($\beta = -0.4273$, $p = 0.0163$).

The lower panel in Figure 3.3 presents the results for the close condition (factories are located in the U.S.). The two-way interaction of moral identity and financial returns disappears ($\beta = 0.1290$, $p = 0.5747$). Furthermore, the relation between moral identity and the WTI in the immoral portfolio in both return conditions is neither negative nor statistically significant regardless of whether the immoral portfolio is incentivized by a higher return. Figure 3.3 provides evidence that the proximity in the close condition induces judgment bias of insensitivity scope, and participants are less sensitive to different levels of financial return when they perceive that the distance is small. Therefore, participants with lower moral identity cannot be incentivized by a higher return level, thus, the WTI in the immoral portfolio does not increase with return incentive level. Our finding further shows that physical distance plays a role in scope insensitivity theory in a financial investment context.

We could also explain the results by recognizing that affective systems focus more on self, and affective feelings are stronger when the target objects are close to the self or the present. Also, individuals care more about people or objects that are physically close to them (Touré-Tillery and Fishbach, 2017), and increased distance lowers moral responsibility and the influence of prosocial action (e.g., Baron & Miller, 2000). If toxic emissions are hurting people close to the self, individuals could have a higher level of empathy. This affects individuals' decision-making by causing them to invest less in the firms that are producing the toxic emissions.

3.3.3.4.3 After-test

It is possible that people with a low moral identity are more likely to invest in an immoral portfolio when toxic emission factories are built in Russia simply because of their low moral rating. Or, they may make such an investment because Russia does not have effective environmental regulations, and this allows companies to lower cost on environmental protection, lower exposure to environmental litigation and thus make more profit. In other words, the investment behavior could be influenced by either a low moral rating or lower environmental regulations in Russia, but not because of the distance proximity. To rule out this possible explanation, we recruited 181 participants and asked them to rate the felt distance, moral rating, and environmental regulations for a list of countries, including France, South Korea, Sweden, U.S., Denmark, Japan, South Africa, Germany, Russia, Norway, Mexico, Finland, and Poland. Our test reveals that the participants only perceive the significant difference in distance between Russia and U.S., but no difference in moral rating or environmental regulations. This test helps us to rule out the alternative explanation of moral rating or perception of environmental regulations in our model.

3.4 Discussion

We observe a three-way interaction among moral identity, financial return, and physical proximity. In the distant condition (when the immoral factory is located in Russia), the two-way interaction of moral identity and expected financial returns suggests that higher financial returns will induce the participants with low moral identity to invest in an immoral portfolio. However, the two-way interaction disappears when participants perceive the distance to the immoral factory is small (when the polluting factory is located in U.S.).

3.4.1 Limitations and Future Research

This chapter examines the moderating role of financial return and physical distance for individuals making ethical financial decisions. We employ a large sample of human subjects to test our full model in Study 3; however, our manipulation of portfolio investment is conducted in the technology sector only. Future studies are needed to see if this finding is evident in different sectors. In addition, we focus only on the effect of perceived distance on ethical decision-making. Chang and Pham (2018) suggest that both *physical* distance and *psychological* distance triggers scope insensitivity. Therefore, in future research, we will explore the impact of physical distance, psychological distance on financial decision-making.

3.4.2 Implications for Business Practice

This chapter identifies some practical implications regarding ethical decision-making and moral investments. When firms deal with unethical portfolios, managers need to consider the utility contributed by both financial returns and morality perspectives. In addition, the physical distance between investors and the headquarter location of the company or the location of immoral factories also plays a role in investors' decision-making.

In this chapter, we use experimental studies to investigate how individuals deal with unethical decision-making. We further investigate the joint moderating effects of financial returns and investors' perceptions of distance from a company's immoral factory on the relation between investors' moral identity and unethical decision-making. Our three-way interaction suggests that decisions of individuals high in moral identity are not affected by either the level of financial returns or the distance to the immoral factory: For these people, the WTI in an unethical investment remains low regardless of the level of financial returns or physical distance. In contrast, when participants who are lower in moral identity perceive they are far away from an immoral factory, they have a higher willingness to make an unethical investment when the expected return is high. When participants perceive they are close to the immoral factory, the significant negative relation between moral identity and unethical investment disappears. This finding could be explained by the moderating role of distance in the scope insensitivity phenomenon. Individuals are more sensitive to financial returns when they are distant from an immoral factory, therefore, they are more motivated to invest in this immoral portfolio due to the higher return incentive. Thus, the WTI in an immoral portfolio is higher. Individuals are insensitive to financial returns when they are close to the immoral factory, and their WTI in this portfolio does not increase even though there is a higher financial incentive.

3.5 Connection to Chapter 4

In this chapter, we examined the individual differences in ethical decision making, and we learned that individuals' moral characteristics significantly impact their financial decisions. Individuals' financial decisions are also closely related to human health conditions, and health shocks could have a devastating negative impact on human wealth. For example, the eruption of the Covid-19 pandemic changes our understanding about the way we view the stock market, and it not only affects stock market performance but also influences the economy through its impact on human capital. Therefore, in the next chapter, we study the health induced human capital. We develop an index, which is constructed by using the search volume of health related symptoms (negative health concerns) to measure *ex ante* health perception in U.S.. Then we proceed to empirically examine the importance of our health index in asset pricing.

Appendix

Appendix 3. 1 Moral Identity Measure (Aquino and Reed, 2002)

Listed below are some characteristics that may describe a person:
Caring, compassionate, fair, friendly, generous, helpful, hardworking, honesty, and kind.
The person with these characteristics could be you or it could be someone else. For a moment, visualize in your mind the kind of person who has these characteristics. Imagine how that person would think, feel, and act. When you have a clear image of what this person would be like, answer the following questions.

	Strongly disagree 1						Strongly agree 7
It would make me feel good to be a person who has these characteristics.	◯	◯	◯	◯	◯	◯	◯
Being someone who has these characteristics is an important part of who I am.	◯	◯	◯	◯	◯	◯	◯
The kinds of books and magazines that I read identify me as having these characteristics.	◯	◯	◯	◯	◯	◯	◯
I would be ashamed to be a person who has these characteristics.	◯	◯	◯	◯	◯	◯	◯
Having these characteristics is not really important to me.	◯	◯	◯	◯	◯	◯	◯
I strongly desire to have these characteristics.	◯	◯	◯	◯	◯	◯	◯
I often wear clothes that identify me as having these characteristics.	◯	◯	◯	◯	◯	◯	◯
The types of things I do in my spare time (e.g., hobbies) clearly identify me as having these characteristics.	◯	◯	◯	◯	◯	◯	◯
The fact that I have these characteristics is communicated to others	◯	◯	◯	◯	◯	◯	◯

by my membership in certain organizations.							
I am actively involved in activities that communicate to others that I have these characteristics.	○	○	○	○	○	○	○

Appendix 3. 2 Survey question for Study 1

You are asked to invest $10,000 in the stock market. After some analysis, you came up with the following two portfolios in which you are considering to invest:

Portfolio 1: This portfolio consists of stocks, which are involved in pornography industry. When investing in this portfolio, the expected return over the next 12 months is 10%.

Portfolio 2: This portfolio consists of stocks, which are involved in the airline sector. When investing in this portfolio, the expected return over the next 12 months is 6%.

The two portfolios are equally risky.

In which of the two portfolios would you prefer to invest?

Appendix 3. 3 Survey question for Study 2

You are asked to invest $1,000 in the stock market. After some analysis, you came up with the following two portfolios in which you are considering to invest:

Portfolio 1: This portfolio consists of stocks, which are involved in firearms industry. When investing in this portfolio, the expected return over the next 12 months is 6%.

Portfolio 2: This portfolio consists of stocks, which are involved in construction industry. When investing in this portfolio, the expected return over the next 12 months is 6%.

The two portfolios are equally risky.

In which of the two portfolios would you prefer to invest?

Appendix 3. 4 Survey question for Study 3

You work as a portfolio manager for an asset management company. You have up to $10,000 to invest in the stock market on behalf of your client. After some analysis, you came up with the following portfolio in which you are considering to invest:

The portfolio consists of stocks of companies that are involved in the Technology industry. These companies develop and manufacture technology products, which have been positively reviewed by the media. All companies in this portfolio established their factories in the United States. The media has criticized these companies regarding toxic emission from their factories.

Technical information about the technology portfolio:

- The portfolio beta is 0.98, and the return standard deviation is 20%.
- When investing in this portfolio, the expected return over the next 12 months is 10%.

Would you like to invest your client's money in this portfolio?

Table 3. 1 Summary Statistics

This table presents the summary statistics for the sample data in Studies 1, 2, and 3. Female indicates the number of female participants in the sample, Age reports the average age for all participants in each sample data, and Caucasian indicates the race. We also report the average moral identity across all participants for each study. Unethical Decision reports the number of participants choosing to invest in an immoral portfolio.

	Study 1	Study 2	Study 3
Female	38	95	251
(%)	(46%)	(49%)	(47%)
Age	21.67	21.85	21.85
(std. Dev.)	(1.958)	(3.080)	(4.089)
Caucasian	55	123	275
(%)	(66%)	(63%)	(51%)
Moral Identity	4.564	4.544	4.375
(std. Dev.)	(1.033)	(0.983)	(1.146)
Unethical Decision	54	46	335
(%)	(65%)	(24%)	(62.5%)

Table 3. 2 Logistic Regression Estimation Results

This table presents the results of logistic regressions in Study 1, Study 2, and Study 3. The dependent variable is a category variable (equals 1 if the respondents choose to invest in immoral stocks). The respondents' moral identity is denoted as MI, which is a continuous variable. The variable Return is a dummy variable (equals to 1 if the portfolio is associated with a higher return, and 0 otherwise). MI*Return represents the interaction variable of moral identity and the return variable. The variable Distance is also a categorical variable (equals to 1 if the location of the immoral company is distant and equals to 0 if the location of the immoral company is close). MI*Return*Distance indicates the three-way interaction variable among moral identity, financial return, and distance. The parentheses show the standard error for the estimated coefficients. The symbols ***, **, * indicate statistical significance at 1%, 5%, and 10 % levels.

	Study 1		Study 2		Study 3	
	(1)	(2)	(3)	(4)	(5)	(6)
MI	-0.515**	-0.565**	0.221	0.221	0.051	0.051
	(0.245)	(0.251)	(0.264)	(0.265)	(0.162)	(0.163)
Return			5.360***	5.332***	-0.678	-0.677
			(1.858)	(1.858)	(1.009)	(1.009)
MI*Return			-0.719*	-0.710*	0.129	0.129
			(0.398)	(0.398)	(0.230)	(0.230)
Distance					-0.263	-0.259
					(0.979)	(0.981)
MI*Distance					-0.025	-0.026
					(0.219)	(0.219)
Return*Distance					3.136**	3.132**
					(1.480)	(1.481)
MI*Return*Distance					-0.582*	-0.581*
					(0.325)	(0.325)
Control (female)		-1.147**		0.148		-0.013
		(0.498)		(0.384)		(0.183)

Figure 3. 1 Conceptual Model

This figure reports the conceptual model we used to test Hypothesis 3, and we examine the moderating roles of financial return level and distance on the relation between model identity and unethical decision-making.

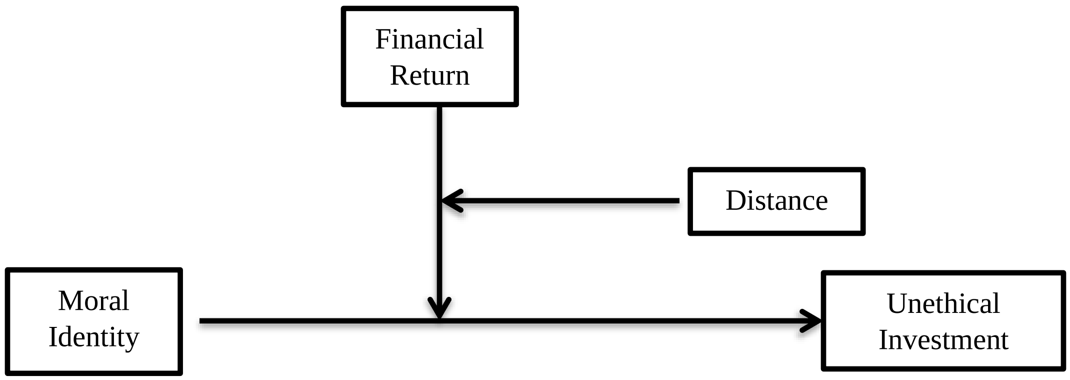


Figure 3. 2 Study 2 Analysis

This figure provides the analysis for examining the moderating role of financial return incentive on the relation between moral identity and unethical decision-making (Study 2). Participants were asked to choose between immoral stocks (firearms industry) and neutral stocks (construction industry). This is a 2 (moral identity: high vs low) by 2 (return condition: 8% expected return vs 6% expected return).

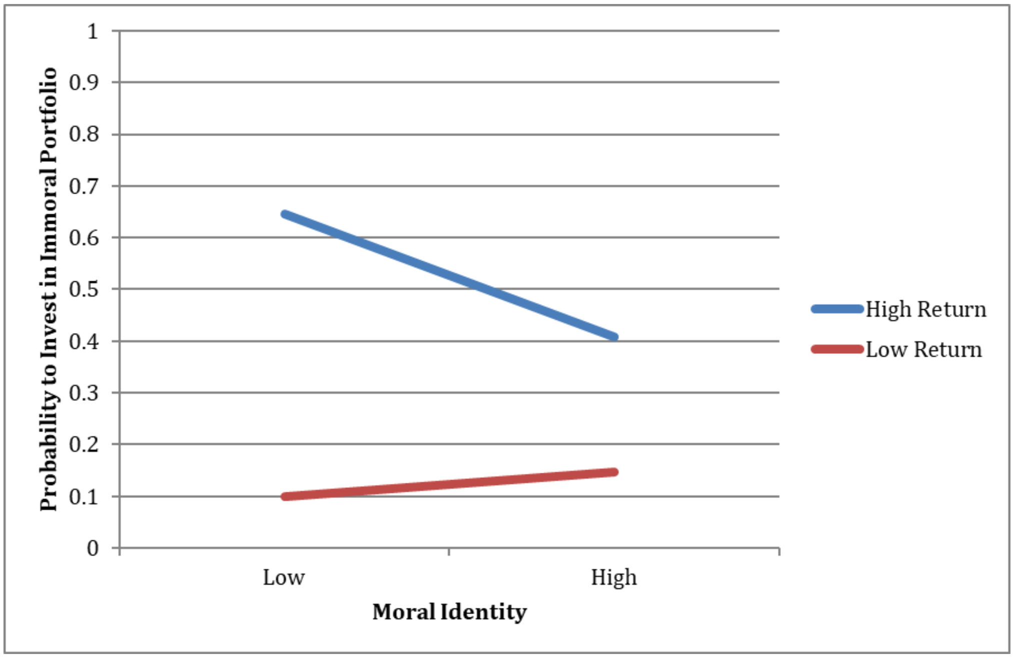
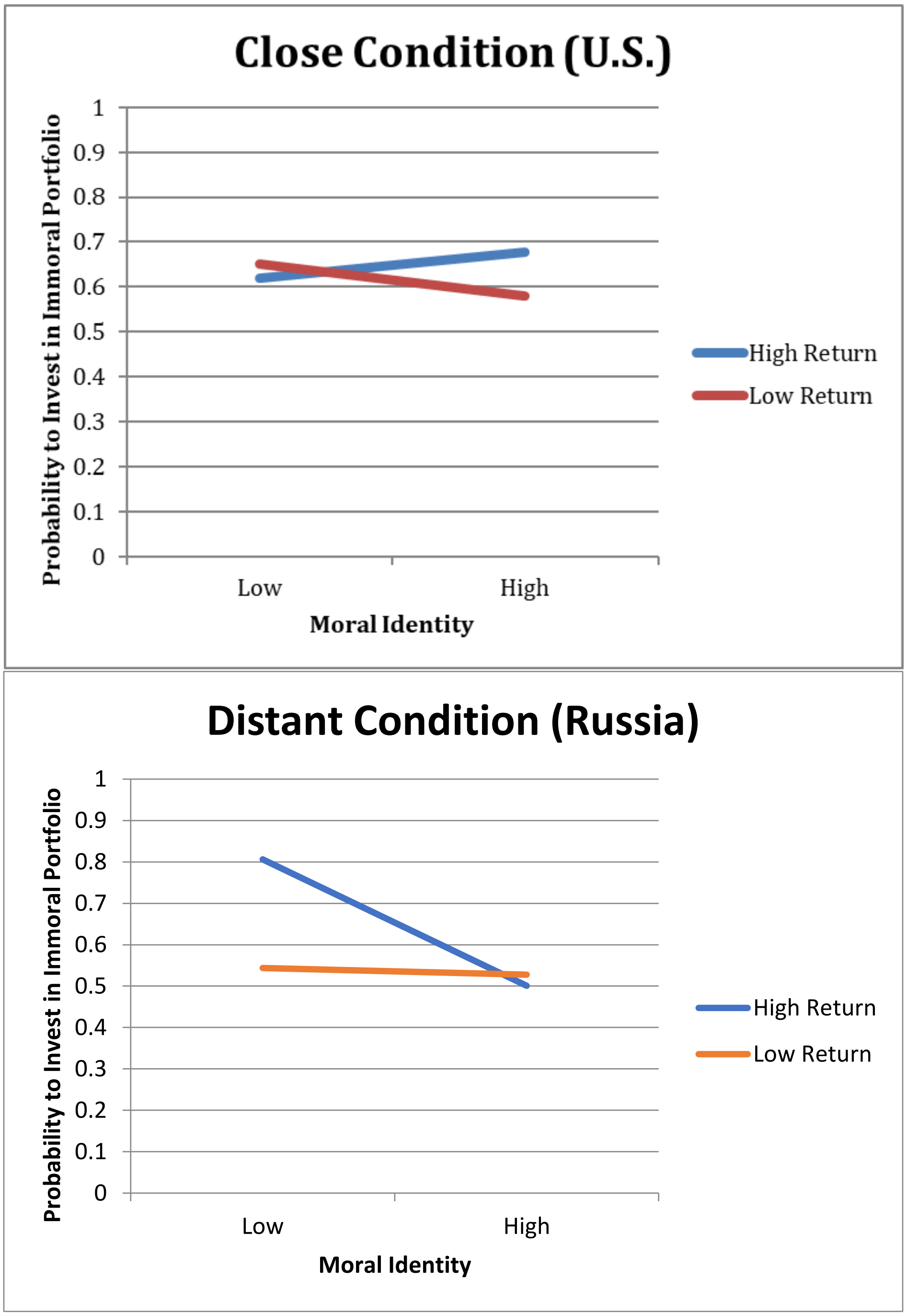


Figure 3. 3 Study 3 Analysis

This figure provides the analysis for examining how financial return incentive and physical distance moderate the relation between moral identity and unethical decision-making (Study 3). We asked participants about their willingness to invest in companies with toxic emissions from their factories. This is a 2 (moral identity: high vs low) by 2 (return condition: 16% vs 10%) by 2 (distance condition: Russia vs U.S.) between-subjects study. The distance condition is manipulated using factories that have toxic emissions located in either Russia (distant condition) or the U.S. (close condition).



4. Ex-ante Health Perceptions and Asset Prices

4.1 Introduction

The Covid-19 pandemic has affected both stock market performance and the economy through its impact on human capital. The state of the economy presents a challenge to policy makers, investors, and households. Human capital depreciation and individual well-being are important and have an impact on the stock market. Human capital, defined broadly, is the individuals' collective knowledge, abilities, skills and other characteristics that related to the achievement of economic outcomes (Becker, 1964; Somaya, Williamson and Lorinkova, 2008; Wright and McMahan, 2011). Even through human capital is not a tradable asset, it significantly contributes to individual wealth (e.g., Heaton and Lucas, 2000; Lustig, van Nieuwerburgh, and Verdelhan, 2013). Palacios (2015) derives a general equilibrium model to study the implications of human capital. Calibrating Palacio's model with the historical wage-to-consumption ratio shows that human capital accounts for 93% of aggregate wealth. Therefore, it is not sufficient to consider only equity returns when we measure the total capital in the economy; rather, it is necessary to include human capital return (Mayers, 1972). In addition, individuals aim to maximize their expected utility of wealth to determine their optimal portfolios, while human capital accounts for a significantly large portion in total wealth, it plays an important role in portfolio choice and asset pricing (e.g., Jagannathan and Wang, 1996; Campbell 1996; Palacios-Huerta, 2003; Lustig and van Nieuwerburgh, 2008; Eiling 2013). Therefore, taking human capital into account when pricing assets is necessary.

Human capital is multifaceted, and health is one vital dimension of human capital (Bleakley, 2010). Becker (2007) develops a model and discover the optimal investment in lowering mortality to study the value of life. The paper points out the importance of health as human capital. In addition, the evidence in the literature shows that individuals' health condition (physical and mental) is significantly associated with human capital (e.g., Currie and Stabile, 2006; Victora, Adair, Fall, Hallal, Matorell, Richter, Sachdev, 2008). Previous studies (e.g., Jaganathan and Wang, 1996; Eiling, 2013) focus on the labor income perspective of human capital, the research studying the impact of health as human capital on asset pricing is scarce. To fill this research gap, in this chapter we study human capital from the health perspective, in particular individuals' *ex ante* health perceptions. To take account of health-induced human capital (HHC) in asset pricing, we assume that the return on human capital is positively and linearly associated with worker perceptions of their health condition. A higher *ex ante* health perception in the labor force increases the rate of return on human capital, which then further affects assets' return.

To study the health dimension of human capital, we first need to quantify human capital in terms of *ex ante* health perceptions of the labor force. We therefore develop a health index, which is constructed using the aggregate level of individuals' perceptions of health concerns. The health concerns are measured by the search volume of medical symptoms on Google's search engine. We first download a list of medical symptoms from the most popular medical websites in the U.S. (e.g., the Mayo clinic, Medline plus, Family doctor.org., and Healthline). We then follow the methodology of Da, Engelberg and Gao (2015), which applies the Google Trends search volume to certain negative terms (words) to construct a sentiment index. Our health index captures the change of aggregate level individual perceptions about health concerns. The higher the level of the index, the higher the search volume for medical symptoms, which result in a lower level of perceived health for the overall labor force. Since our index of health concerns is negatively related to individuals' good health perceptions, we multiply the index by (-1) to obtain a positive proxy for individual human capital for the health dimension, denoted as health-induced human capital (HHC).

Next, we empirically test the implications of our HHC index in the cross-section of stock returns. First, we estimate the stocks' exposure to human capital; specifically, we regress the excess returns on individual stocks on our HHC using a backward rolling regression with a 24- month fixed window, and then obtain firm-level loadings (betas) with respect to the health perspective of human capital. Next, we run a univariate analysis to examine the portfolio performance of HHC beta portfolios. While the lowest and negative HHC beta portfolio contains stocks whose returns are negatively correlated with the increase of human capital on the health dimension, the high and positive beta portfolio includes stocks whose returns are positively correlated with individuals' health perceptions.

The literature demonstrates that the expected returns of securities have a positive linear relation with the covariance between a security's return and the return on human capital (e.g., Jaganathan and Wang ,1996; Eiling, 2013; Palacios 2015). Our empirical analysis provides consistent evidence for the existing theory, i.e., stock exposure to the HHC is positively related to equity returns. A univariate portfolio sorted based on HHC betas suggests that the highest HHC beta portfolio significantly outperforms the lowest beta portfolio, demonstrating that the expected asset returns have a positive relation with HHC beta. The results imply that investors demand an extra premium to hold stocks that earn a lower return when the market-level *ex ante* health perception is low. In other words, investors prefer assets that perform well while the aggregate health perception is low in the market as a whole, which serves as a hedge for the low market-level health perception (higher *ex ante* health concerns). For example, during the Covid-19 pandemic, the *ex ante* health perception in general is low (e.g., individuals may worry about symptoms like a sore throat or fever because that may suggest that they have contracted the coronavirus). Investors are more willing and comfortable to hold stocks that perform well during the pandemic. In addition, we adopt Fama and MacBeth (1973) regression to examine the pricing of our HHC index. We find that *ex ante* HHC carries a positive and significant risk premium. Therefore, our empirical results are consistent with theoretical evidence regarding human capital.

While the literature has widely used the growth rate of labor income as a proxy for human capital, research on the health dimension of human capital is scarce. To our knowledge, there is no appropriate proxy to capture the health-induced changes in human capital covering an adequate length of time for the U.S. population. The existing human capital indices (e.g., the human capital index from the World Bank and Blue Cross/Blue Shield health index) are either country-level annual data or cover a short sample period. We contribute to the literature on human capital in three ways: (1) we construct a high frequency health index which describes *ex ante* human health perceptions across time; (2)

we study how HHC impacts the equity market; and (3) we price human capital in terms of the perception of health conditions in asset pricing.

The remainder of this chapter is organized as follows: Section 3.2 provides theoretical evidence regarding the implications of human capital on the health perception dimension in asset pricing. In Section 3.3, we explain the construction of our *ex ante* health perception index. Section 3.4 describes the data and methodology used for testing the role of our health index on cross-sectional stock returns. The empirical results and additional robustness tests are reported in Section 3.5, and Section 3.6 concludes the chapter.

4.2 Theoretical Evidence

Studies examining how human capital impacts equity returns can be traced back to Mayers (1972); the study considers not only marketable assets but also non-marketable assets in the asset pricing model. The author proposes that the payoff for non-marketable assets (e.g., the rate of return on human capital) can be appropriately proxied by the income earned by labor. To empirically test the relation between human capital and financial assets, Baxter and Jermann (1994) use labor income as a proxy for human capital return; they find that human capital return has a correlation of .94 with the stock market return in monthly data. Benzoni, Collin-Dufresne and Goldstein (2007) discover that the market return and return on human capital are cointegrated. Palacios-Huerta (2003) applies the rate to schooling (marginal rate of earing in terms of highest education) as a proxy for the return of human capital and finds that investing in high level education (e.g., high school and college) generates a significantly higher return than investing in financial assets.

Human capital is priced in the cross-section of equity returns through the covariance between equity return and the return of human capital (e.g., Baxter and Jermann, 1997; Bansal, Kiku, Shaliastovich, and Yaron, 2014; and Lustig and Van Nieuwerburgh, 2008). Jaganathan and Wang (1996) propose that the market return is a linear function of both stock index portfolio return and human capital return. By using the growth rate in per capita labor income as a proxy for the return on human capital, they incorporate human capital into an asset pricing model (APM). They measure the stock exposure to the labor beta, which is estimated as the covariance between individual stock return and human capital return. Their model suggests that the labor beta is positively associated with the expected stock return. In addition, they empirically show that the human capital adjusted APM better explains the variation in the cross-section of individual equity returns. The heterogeneity in human capital across different industries has also been studied. After first determining the industry-specific labor income risk (which is measured as the covariance between asset return and growth rates of labor income in each industry), Eiling (2013) finds that industry- level human capital has a significant impact on the cross-section of stock returns. Palacios (2015) construct a three-factor model by incorporating labor shares and investment in human capital into the APM. Assuming that the return of wealth is a function of the return on human capital, the author suggests that investing in human capital generates payoffs (e.g., wages) similar to investing in a security. Thus, human capital return affects the stochastic discount factor and further impacts the risk premium of an asset through the covariance between security return and the return of human capital. The evidence revealing that stocks with higher exposures to human capital returns are associated with higher conventional risk-adjusted returns further confirms that human capital is positively priced in asset pricing.

It is challenging to quantify a firm's human capital level. The return on human capital is not observable or directly measured. Therefore, the literature commonly uses the growth rate of labor income as a proxy for firms' human capital (e.g., Jaganathan and Wang, 1996; Qin, 2002; Eiling, 2013). The labor force is the input of firms, and firms use workers' knowledge and skills to produce and generate wealth. Thus, the growth rate of labor income is a popular proxy for the rate of return on human capital. However, human capital has several different dimensions such as knowledge, skills, and health (e.g., Becker, 1964; Becker, 2007; Bleakley, 2010), and labor income does not capture these other dimensions.

"Health is both human capital itself and an input to producing other forms of human capital" (Bleakley, 2010, p. 283). Health shock or disease affects workers' abilities (mental or physical) and decreases labor's productivity. For example, the Covid pandemic increases health-induced disruptions at work, and incurs a human capital loss (Acharya, Johnson, Sundaresan and Zheng, 2020). The *ex ante* health perception directly affects the supply of labor and the quantitative effort devoted to work. Workers exposed to health shocks such as sickness or other medical concerns are directly (and negatively) affected in terms of their ability to work and to participate in the labor force. Severe health shocks may force them to completely exit from the labor market. While the shock to the *ex ante* health perception lowers human capital, the change in individual health perceptions negatively affects the rate of return for human capital. To better understand the health dimension of human capital, it is necessary to empirically measure market-level individual health perceptions. Some research shows that early childhood health conditions (e.g., health conditions from the prenatal period to the age of five years) significantly affect adult human capital (e.g., Almond, 2006; Victora et al., 2008; Almond and Mazumder, 2011). In addition, Hong, Wang, and Yang (2020) study the pandemic risk via the COVID-19 transmission rate and find that aggregate transmission shocks significantly affect asset pricing.

Studies that examine the impact of the health dimension of human capital on asset pricing are scarce since there is no appropriate proxy for the individual's health as human capital. But we can capitalize on the fact that when individuals have a perception that their health is at risk, they may search online or browse medical websites to find information, advice, and solutions. For example, a person with itchy eyes might do a Google search for "eye infections," or a woman with breast pain might search for symptoms of "breast lump", "breast cyst" or even "breast cancer". Search volume data from Google Trends therefore provides us with an opportunity to construct a market-level health index which might capture a general *ex ante* health concern. While searching for medical symptoms does not necessarily mean that a person has a disease (e.g., one person searching for "breast cancer" does not necessarily mean that the person has breast cancer), the searching volume of medical symptoms is a proxy for the *ex ante* perception of health concerns. The HHC measure in our research is defined as the inverse of health perception concerns, therefore the higher the HHC, the lower the search volume of medical symptoms (the lower the *ex ante* health concern perception).

Since health perception is an important component of human capital, the aggregate market-level health perception enters the utility function of wealth and plays an important role in asset pricing. The economic mechanism behind the pricing of HHC is that, *ex ante*, health perception has an impact on an individuals' consumption decision and investment choices. When people are more concerned about their health, they will alter their future consumption and their portfolio choice will also be affected. Therefore, the *ex ante* health perception is a potential state variable in an asset pricing model. Consistent with human capital asset pricing models in the literature, we assume that our HHC index has a positive and linear relation with the return on human capital (the higher the HHC, the higher the human capital return). While the CAPM captures a positive risk premium on the market factor, we take account of the health dimension of human capital in the asset pricing model. We believe that the expected return of an asset is positively correlated with equity market beta and an additional human capital beta, where the market beta is measured as the covariance between the asset return and the market portfolio return, and the human capital beta is the covariance between the return of this asset and the return on human capital in the health dimension. While the theoretical evidence suggests that human capital return carries a positive risk premium, our health induced human capital measure is also expected to be priced positively.

The explanation is that investors demand extra compensation for holding stocks that positively covary with the aggregate health perception, since these stocks earns a lower return when the market-level health perception is bad. In other words, investors prefer to hold stocks with a negative covariance with the aggregate health perception, since negative health beta stocks tend to perform better when the market-wide *ex ante* health perception is low. Investors could use negative beta stocks to hedge against this economy-wide poor health perception.

4.3 Health-induced Human Capital (*Ex ante* Health Index)

In this section, we explain how we construct the health-induced human capital, and then test the impact of our health index on equity returns.

4.3.1 The HHC Index

To empirically study health induced human capital, we first construct a health index as a proxy for the health dimension of human capital. Following Da, Engelberg and Gao (2015), we start by determining a list of medical symptoms. We obtain the medical symptom lists from the most popular medical websites in North America. Specifically, we obtain 153 terms from the Mayo Clinic, 94 terms from Medline Plus, 46 terms from Family doctor.org, and 79 terms from Healthline (Denecke and Neidl, 2009; Heim, 2010; Morgan and Montagne 2011; Tran, Singh, Singhal, Rudd, and Lee, 2017). The medical symptoms include "abdominal pain," "breast lumps," "cough," "Dysuria," etc. Some of the terms have an alternative name; for example, the symptoms of Anosmia also refer to the loss of smell (from the website of the Mayo Clinic). We obtain terms with alternative names, integrate all of the medical terms from the four websites, and then delete duplicates terms. This results in 272 terms. Next, we exclude the search terms with low number of observations (N < 1000) and are left with 236 terms.

We next downloaded the daily search volume of each of the 236 medical terms from Google Trends. Since Google Trends started to report search volume in 2004, our sample covers the period between January 01, 2004 and Dec 31, 2019. In addition, Google Trends provides the relative search volume (not the realized search volume) in the query window frame. The daily search volume was downloaded on a monthly basis.

Next, we take the logarithm of the relative search volume and define the daily change in search term *i* on day *t* as $\Delta SV_{i,t} = \ln(SV_{i,t}) - \ln(SV_{i,t-1})$. We then adjusted the daily change of search volume with the following three steps: (1) winsorize the daily change at the 5% level (2.5% in each tail) to control for outliers; (2) de-seasonalize our data to address the seasonality issue (regress $\Delta SV_{i,t}$ on weekday and month dummies and keep residuals); and (3) scale each $\Delta SV_{i,t}$ by the time series standard deviation to standardize our data (e.g., Baker and Wurgler, 2006). We finally obtain the adjusted daily change of each search volume $\Delta XSV_{i,t}$ for each medical term.

We next determine the medical terms that comprise our health index by finding the terms which have the most negative impact on market returns. The index returns are returns of the S&P 500 index obtained from the CRSP. We then conduct a backward rolling regression with a 6-month fixed window and regress our adjusted daily change of search volume for each term on the market index return to obtain the coefficient estimates. The coefficients for month t are based on the daily regression results during sample periods between t-1 and t-6. Then we sort all terms based on the t statistics of the estimated coefficients; the 30 terms with the lowest t statistics are the terms we use to construct our heath index for time t. The equation of the health index is defined as $Health\, Index_t = \sum_{i=1}^{30} T^i(\Delta XSV_t)$, where $T^i(\Delta XSV_t)$ presents the ΔXSV_t for one of the 30 terms which have the most negative impact on the stock market. The aggregate of the adjusted daily search volumes of these thirty terms is used to determine the next month's health index. Table 4.1 reports the 30 terms with the most negative impact on the stock market during January 2008 and June 2008. We then construct the health index for July 2008 based on the total value of the adjusted daily change of search volume for these 30 terms. The first three terms in Table 4.1 are leg pain, nosebleeds, and headache, with t statistics of -2.41, -2.03 and -1.88, respectively. This suggests that these three medical symptoms had the most negative impact on the market during January 2008 and June 2008.

4.3.2 HHC Index and Market Average Returns

Since our health index constructed in subsection 3.3.1 measures the negative health perception (health concerns), we then multiply our *ex ante* concern indicator by (-1) to proxy the positive health perception, and we denote the inverse of the concern indicator as HHC. When individuals in the whole economy experience *ex ante* health concerns or negative health perceptions, HHC decreases, which results in a health shock to the market (e.g., the Covid-19 crisis). This shock is not captured by fundamentals, but it could have a long-term negative impact on the market, thus, we expect to observe a downturn in the market index returns. Therefore, we predict that there is a positive relation between the individual's health perception (HHC) and market index returns. In other words, the lower the HHC, the lower the return in the market index.

In this section, we run a predictive regression to examine the impact of our health index on the stock market. The regression is listed as follows.

$$r_{t+m} = \delta_0 + \delta_{HI} Health\ Index_t + \sum_n \delta_n\, Control\ Variable_{n,t} + \varepsilon_{t+m} \tag{1}$$

Where r_{t+m} indicates the daily Standard and Poor's 500 (S&P 500) stock return at time $t+m$, and m = 0,1,2,3,4,5. We control for lagged returns and other macroeconomic conditions and investor sentiment, including the Aruoba-Diebold-Scotti business conditions index (ADS), the CBOE volatility index (VIX) and economic policy uncertainty (EPU), To control for market sentiment, we obtain daily market volatility index (VIX)[3] from the Chicago Board Options Exchange (CBOE). VIX measures the option-implied volatility with an underlying asset of the S&P 100 stock index. Also, we adopt a daily index developed by Aruoba, Diebold, and Scotti (2009) (ADS Index)[4] to control for macroeconomic conditions. The ADS index is obtained from the Federal Reserve Bank of Philadelphia and is constructed based on tracking GDP, unemployment, production, manufacturing, sales, etc. In addition, to capture the relation between our health index and the market index, we apply a daily index (denoted as EPU)[5] constructed by Baker, Bloom, and Davis (2013) to control for uncertainly caused by economic policies.

The results for the predictive regressions are reported in Table 4.2. We observe that our health index has a contemporaneous positive relation with market index returns. While $m = 0$, the coefficient estimate is 0.0095 with a t statistic of 2.9454. The economic impact is large as well: a one standard deviation decrease in our *ex ante* HHC index is associated with a decrease of 5.2% daily return in the S&P 500. The positive impact is statistically significant at the 1% level. In addition, we run predictive regression when m = 2, 3, 4, 5. The coefficient estimates are not significant, and we do not report the results (for $m \geq 1$) in Table 4.2.

We also calculate the cumulative returns over the following week [t+1, t+7], the following two weeks [t+1, t+14] and the following month [t+1, t+30]. Then we regress the

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[3] The VIX index is obtained from https://ww2.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index/vix-historical-data.
4 The ADS index is obtained from https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/ads.
5 The EPU index is obtained from http://www.policyuncertainty.com/us_monthly.html.

cumulative returns on our health index; the regression results are reported in Columns (3)-(6) in Table 4.2. The estimates of the coefficient on the *ex ante* perception of health concern are not statistically significant, suggesting that our health index has no explanatory power to predict market return in the following days. This result suggests that our *ex ante* health perception is not a mispricing, and the negative impact of shocks in heath concerns seems to be fundamental since it is not followed by a market correction. This is different from results reported on shocks to the financial and cconomic attitudes revealed by search (FEARS) index (Da, Engelberg and Gao, 2015), which has a temporary negative impact on the S&P 500 returns, followed by a return reversal over the following two days. Sentiment is irrational; therefore, the mispricing is expected to be corrected. In this chapter, we demonstrate that our health concern index has a permanent impact on the market with no subsequent return reversal. In other words, shock to human health perceptions have a permanent impact on the market.

4.4 The Cross-Section of Stock Returns

Human capital plays an important role in asset pricing, and human health contributes significantly to human capital. We denote this inverse health concern index as health induced human capital (HHC) to proxy the health dimension in human capital. Also, we assume the HHC has a positive linear relation with human capital for the health dimension of human capital. In this section, we examine whether our health induced human capital asset pricing model could explain the cross-sectional stock returns.

4.4.1 Data

We obtain the stock returns from the Center for Research in Security Prices (CRSP) and company information from Compustat. Our data include stocks from NYSE, AMEX, and NASDAQ. We exclude stocks that do not have a CRSP share type code of 10 or 11 (e.g., ADRs, REITs). In addition, utility firms and financial firms (SIC codes between 4,900 and 4,999 and between 6,000 and 6,999, respectively) are excluded from the sample. We then eliminate stocks with a share price lower than $5 to only include more liquid stocks.

The health-induced human capital is proxied by our *ex ante* health perception index. The index, which measures the health dimension of human capital is constructed on a daily basis, however, the stock exposure (loadings) will be noisier when it is estimated by regressing daily stock returns on the HHC index. Therefore, we obtain the monthly health index by using the median of the daily health index in each month. Table 4.3 reports the correlations between HHC and other risk factors, including market factor (MKT), size factor (SMB), value factor (HML), momentum factor (MOM), profitability factor (RMW), investment factor (CMA), and liquidity factor (LIQ). Our monthly health index, a proxy for human capital on the health dimension, has a negative and significant correlation only with the liquidity factor, and the correlation is –0.16 with a 5% significance level.

4.4.2 Firm Characteristics

In this section, we describe firm characteristics and their estimation. The natural logarithm of market capitalization is used to describe the firm size (denoted as Size), where the market capitalization is calculated as the product of stock price per share and the number of shares outstanding at month t (Fama and French, 1992). The book-to-market ratio (denoted as BM) at year t is measured as the ratio of the book value at the end of the previous fiscal year to the market value in December of the previous year. Momentum (denoted as MOM) is the cumulative return during month t-1 and t-12 (Jegadeesh and Titman, 1993). The investment variable (denote as IA) is calculated as the percentage of changes in total assets. The idiosyncratic volatility (denoted as Idio Vol) is measured as the standard deviation of daily residuals obtained from the Fama and French (1993) three-factor model within a month (Ang, Hodrick, Xing, and Zhang, 2006). The stock's illiquidity (denoted as ILLIQ), is estimated as the monthly average of daily ratios of the absolute return to the dollar valued trading volume (Amihud, 2002).

4.4.3 Methodology

To test the relation between health-induced human capital and the cross-sectional variation of returns, we first estimate the stock exposure to our health index. We then follow Ang, et al., (2006) and Bali, Brown and Tang (2017) to regress the individual monthly stock excess return of all stocks trading on American Stock Exchange (Amex), the New York Stock Exchange (NYSE), and Nasdaq on the market excess return and the aggregate health-induced human capital. We run a backward rolling regression, and the stock exposure at month t is obtained by regressing returns on the HHC for the past 24-month window. The regression equation is described as follows.

$$r_t^i = \beta_0 + \beta_{HHC}^i HHC_t + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \varepsilon_t^i \quad (2)$$

where r_t^i indicates the excess return for stock i at month t. HHC_t is the aggregate level health index, a proxy for health-induced human capital. MKT_t is the excess return of the market portfolio, SMB_t is the size factor and HML_t is the book-to-market factors (Fama and French, 1993). β_{HHC}^i is the exposure of individual stock *i* on our health index. β_{MKT}^i, β_{MKT}^i, and β_{MKT}^i indicate market beta, size beta, and value beta, respectively.

4.5 Empirical Analysis

In this section, we present empirical analyses that examine the impact of HHC on the cross-section of equity returns. To study the role of *ex ante* human health perception in the cross-section of equity pricing, we first discuss the results of univariate portfolio analyses and portfolio analyses which control for common firm characteristics. We then examine the cross-sectional regressions (Fama-MacBeth, 1973) to study the pricing of the aggregate HHC on the cross-section of expected stock returns.

4.5.1 Univariate Portfolio Analysis

To explore the performance of stock exposure to the HHC on the variation in stock returns, we study univariate portfolios sorted by the HHC betas. The factor loadings (β_{HHC}^i) on health index are obtained from the regression in Equation (2). The regression is conducted with a backward 24-month rolling window approach. The first set of health beta of July 2009 are obtained using monthly stock returns regression from the sample period between July 2007 and June 2009. We sort all NYSE, Amex, and NASDAQ stocks in our sample into five quintiles based on the HHC beta. We then equal-weight the portfolio to obtain five portfolio returns. The results of the univariate portfolio analyses are presented in Table 4.4. The first row (portfolio Low) presents the average return and the factor-adjusted return for the lowest beta portfolio, which includes stocks with the lowest exposure to the HHC index. Portfolio High represents the portfolio of stocks with the highest HHC beta, suggesting the firms in portfolio 5 (High) have a lower return when market-level individual perceptions of their health condition decrease. We also construct a tradable difference portfolio (High minus Low), which is long a portfolio with the highest HHC beta and short a portfolio with the lowest HHC beta.

Columns (1) and (2) in Table 4.4 present the average firm size and book-to-market ratio (BM) for each quantile portfolio. The portfolios with the highest and lowest beta stocks have slightly smaller size, and there is no significant difference in firm book-to-market ratio across the five portfolios. Column (3) reports the portfolio average stock exposure to our HHC index. The portfolio betas increase from -3.00 to 3.15 across the five portfolios. The average returns for each of the five portfolios are reported in Column (4). The cross-sectional variation in the average portfolio returns is significant, moving from the lowest quantile portfolio to the highest health beta portfolio (the monthly return increases from 1.03% to 1.47%). The difference portfolio (High minus Low) generates an average monthly return of 0.44% (or average annual return of 5.28%) with a Newey-West t statistic of 1.95.

In addition to the average quantile portfolio returns, we also calculate risk-adjusted returns (alphas) controlling for several well-known risk factor. Columns (5) to (7) in Table 4.4 present the alphas from several factor models, including the CAPM model, the Fama French three factor model (FF3), the Carhart four factor model (Carhart 4), and the Fama French five factor model (FF5). In addition, Column (8) presents alphas from the factor model controlling not only FF5 factors but also momentum and liquidity factors. When controlling for market factor only (CAPM+HHC), the risk-adjusted return increases from -0.02% to 0.46% per month, moving from the lowest quantile portfolio to the highest quantile portfolio. The difference portfolio generates a 0.48% monthly risk-adjusted return (or 5.76% annually), and it is statistically significant at the 5% level. In addition, the risk-adjusted returns remain positive and significant after controlling for different factors. The statistical significance of the risk-adjusted return in the difference portfolio is attributed to the outperformance of the high β_{HHC} portfolios. The highest HHC beta quantile portfolio significantly outperforms the lowest beta portfolio, suggesting that investors demand extra compensation for holding stocks that perform poorly while the health perception on the whole economy is low, therefore, the expected return in portfolio High is significantly higher.

4.5.2 Portfolio Analysis Controlling for Firm Characteristics

To control for firm characteristics, we also conduct a bivariate portfolio analysis (Ang et al., 2006). When we control for firm size, we first rank stocks based on firm market capitalization and sort them into five quintile portfolios. Within each size portfolio, we further rank stocks based on their exposure to the HHC index and sort them into five portfolios. We obtain 25 size-HHC beta portfolios, and we balance each portfolio monthly. We then calculate the average return across five size quantiles for each of five HHC beta portfolios. Now each HHC quantile portfolio contains all size dispersions. The same method is also applied to control for other firm characteristics (e.g., BM, momentum, and illiquidity). Panels A through Panel D of Table 4.5 report the empirical results for the portfolio analysis controlling for size, BM, momentum, and illiquidity, respectively.

When we control for firm size, the average return spread between the highest HHC portfolio and the lowest HHC beta portfolio is 0.34 per month with a t statistic of 2.35. The risk-adjusted returns in the difference portfolio remain positive and significant after controlling for different risk factors. However, the result in Panel B is weaker when we control for BM. The results in Panels C and D also provide consistent evidence that the highest beta quintile portfolio significantly outperforms the lowest beta portfolio after controlling for momentum and liquidity.

4.5.3 Fama-MacBeth Regressions

To examine the pricing power of human capital for the health dimension, we further apply a two-stage Fama-MacBeth (1973) regression to test whether there is a positive risk premium for our HHC index. We first form 25 portfolios, which are sorted based on the market beta and the HHC beta. In the first stage, we run a time series regression in each of 25 portfolios to obtains factor loadings on all risk factors. In the second stage, we conduct a cross-sectional regression at each time t and regress portfolios returns on factor loadings estimated in the first stage. We then average the time series estimated coefficient on factor loadings to estimate their risk premiums.

The second stage of Fama-MacBeth (1973) regression is described in the following equation:

$$r_t^i = \lambda_0 + \lambda_{MKT}^i \beta_{MKT}^i + \lambda_{HHC}^i \beta_{HHC}^i + \lambda_X^i \beta_X^i + \varepsilon_t^i \qquad (3)$$

where β_{MKT}^i and β_{HHC}^i are exposure of portfolio i (i = 1, 2, … 25) on the market factor (excess market return) and our health index. λ_{MKT}^i and λ_{HHC}^i are the estimates of risk factor premiums. β_X^i indicates the factor loadings on other factors which have explanatory power on stock returns, such as the size factor, value factor, momentum, liquidity, investment, and profitability factors. λ_X^i represents the estimated price premium of risk factor X.

Table 4.6 reports the time series average of coefficient estimates. Column (1) shows that the risk premium of our health index HHC is 1.07% using 25 test assets formed from sorting based on market beta and HHC beta. This suggests that human capital in the health dimension is positively priced. Columns (2)-(6) present the risk premium of our health index in the CAPM model, the FF3 model, the Carhart 4 model, and the FF5 model, respectively. When we control for MKT (CAPM), the price of the HHC is 0.94% with a Newey-West t statistic of 2.26. When we control for FF3 factors, the price of the HHC is 0.84% per month. The risk premium of the HHC remains positive and significant at the 5% level, controlling for Carhart 4 factors and FF5 factors. In column (7), we control for 7 risk factors (five factors from the FF5 model, momentum and liquidity factors), and the positive risk premium of the HHC is significant at 10% level. Table 4.6 suggests that human capital in the health dimension carries a positive and significant risk premium.

4.5.4 Robustness Regressions

In this section, we conduct several additional tests to study the role of our health index on the cross-section of asset returns.

4.5.4.1 Forward Looking Bias

When we construct our health index, we winsorize the time series of search volume for each search term at the 5% level. Since winsorizing is conducted based on the full sample data, this procedure may create a forward-looking bias. To address this issue, we re-construct the health index without winsorizing the data. We then run a predictive regression in Eq (1) using the normalized HHC, and the results show that the normalized HHC has a positive contemporaneous relation with S&P 500 stock return (the coefficient estimate is 0.0090 with a t statistic of 2.77). The positive relation is statistically significant at 1% level. This result is consistent with the coefficient estimates listed in Table 4.2. Next, we obtain the monthly HHC and follow the same procedure in section 3.5.1 to examine the impact of this HHC constructed without winsorization on the cross-section of returns. The regression results in the univariate portfolio analysis are reported in Table 4.7, and the average return spread and risk-adjusted return spread in the difference portfolio (High-Low) are consistent with the results from the original HHC.

4.5.4.2 Alternative Health Index

Google Trends provides relative search volume (RSV) for each search query, and each RSV is indexed between zero and 100 for a selected search time frame. Zero represents the lowest relative search interest for a given search term and 100 indicates the maximum search interest. Furthermore, time series RSVs for the same term vary with different selected search time frames, since the maximum search interest changes over time. In addition, only search queries with less than 9 months time frame generate daily data, thus, we need to submit multiple search queries to obtain the full sample daily RSVs. The potential issue is that the RSVs of the same term are not comparable across different search queries due to the change of maximum search interest.

In this chapter, we download the daily data on a monthly basis, and RSVs of each term are comparable within a month, but not comparable across months. We take the logarithm of the daily search volume and then take the first difference to track the daily change in search volumes, but the invalid intra-month comparison issue is not fully addressed. To allow intra-month comparisons, we also download monthly RSV data, and each term is indexed monthly between zero and 100 over the full sample period. We then normalize the daily data by multiplying the daily RSV by the corresponding monthly RSV ratio, which is calculated as the monthly RSV divided by 100 (the highest monthly RSV over the sample period). We then follow the same procedure described in section 2 to construct our health index (HHC). The normalized HHC and the original HHC are highly correlated, and it is also negatively associated with the return of S&P 500 index (coefficient estimate is -0.0089 and t statistic ois-2.75). The negative relation is statistically significant at 1% level, and this result is consistent with the coefficient estimates listed in Table 4.2. The normalization procedure fully addresses the comparison issue, but it does introduce a potential forward-looking bias.

4.6 Conclusion

In this chapter, we construct a human capital index which measures the *ex ante* health perception in U.S. We first obtain a list of medical symptoms from four of the most popular medical websites: the Mayo Clinic, Medline Plus, Family doctor.org, and Healthline. Then we aggregate the search volume obtained through Google Trends for terms which have the most negative impact on S&P 500 market index returns. We then use the inverse of our medical symptoms-based health indicator as a proxy for human capital in the health dimension (HHC). We find that our HHC index has a significant positive relation with the market index. Specifically, lower the index, higher the level of *ex ante* perception in medical concerns, thus, the lower the market-wide stock return. The economic impact is large as well: a standard deviation decreases in our daily health perception index results in a contemporaneous decrease of 5.2% in daily stock market returns.

The HHC index we constructed allows us to study the health dimension of human capital and helps us to fill the research gap by examining the impact of the health dimension of human capital on the cross-section of portfolio and individual stock returns. To estimate the stock exposure to our HHC index, we first take the median of the daily HHC index within each month to obtain the monthly HHC index. We then regress monthly individual stock returns on the HHC index using a backward rolling regression with a 24 fixed monthly window. We then form five quantile portfolios by sorting stocks based on their HHC betas. The univariate portfolio analysis reveals a positive and significant return spread of 0.5% per month between the lowest and highest beta quantile portfolio. After controlling for conventional risk factors, the lowest beta portfolio generates a significantly higher factor-adjusted return compared to that in the highest beta portfolio. The results are robust when we control for different firm characteristics. To examine the pricing of our health index, we conduct Fama and Macbeth (1973) cross-section regressions. Our regression results confirm that our HHC index carries a positive and significant risk premium. Our findings are consistent with the human capital asset pricing literature. Human capital is priced in equity returns through the covariance between individual equity return and the return on human capital. Our results imply that investors demand an extra premium to hold stocks which generates a lower return when individuals' health perceptions in the economy decrease.

Table 4. 1 Medical Symptoms List used in the Health Index

This table reports 30 medical symptoms that were used to construct the health index (human perception on health concerns) for July 2008. We run backward rolling daily regressions by regressing S&P 500 returns on each medical symptom over the sample period between January 2008 and June 2008. The 30 terms with the most negative impact (the lowest t-statistics) on the market index return are used to construct the health index for the next six months.

	Search Term	**T-Statistics**
1	Leg pain	-2.41
2	Nosebleeds	-2.03
3	Headache	-1.88
4	Nasal congestion	-1.82
5	High red blood cell count	-1.79
6	Numbness	-1.71
7	Hypokalemia	-1.64
8	Joint pain	-1.57
9	Kernicterus	-1.49
10	Loss of smell	-1.45
11	Hearing problems	-1.43
12	Toothache	-1.37
13	Facial swelling	-1.37
14	Tachypnea	-1.33
15	Breast calcifications	-1.31
16	Peripheral edema	-1.30
17	Eye pain	-1.19
18	Skin Problems	-1.11
19	Dehydration	-1.07
20	Bruises	-1.06
21	Edema	-1.06
22	Chronic pain	-1.05
23	Nipple discharge	-1.04
24	Obesity	-1.04
25	Cold hands	-0.98
26	Pain	-0.96
27	Teeth grinding	-0.95
28	Hyperuricemia	-0.93
29	High potassium	-0.92
30	Wasp sting	-0.92

Table 4. 2 *Ex ante* Health Perception and S&P 500 Returns

We regress S&P 500 daily returns on our *ex ante* health index, which is constructed based on the search volume of medical symptoms. Our health index measures the aggregate level health concerns. Column (1) reports the contemporaneous regression, and the dependent variable is the daily return of the S&P 500 index at time t. The dependent variable in columns (3)-(6) represents the daily cumulative returns. In each regression, we control for VIX, EPU, ADS and lagged index returns (lag1-lag 5). The t-statistics for coefficient estimates are described in parentheses. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)
	Ret (t)	Ret (t+1)	Ret [t+1, t+7]	Ret [t+1, t+14]	Ret [t+1, t+30]
HHC Index	0.0095***	-0.0038	-0.0058	-0.0084	-0.0176
	(-2.9454)	(1.1664)	(0.7409)	(0.7751)	(1.1725)
VIX	-0.0407***	-0.0406***	0.0555***	0.0977***	0.2056
	(-13.3418)	(-13.3030)	(7.4180)	(9.4707)	(14.3578)
EPU	0.0020***	0.0019***	-0.0032***	-0.0033***	0.0010
	(6.3355)	(6.1738)	(-4.2479)	(-3.1672)	(0.6870)
ADS	-0.1737***	-0.1773***	0.7879	1.6022**	3.4815***
	(-5.6909)	(-5.8044)	(10.6742)	(15.7320)	(24.6357)
Ret_lag	-0.1297***	-0.1314***	-0.0878**	-0.1040**	0.0200
	(-8.1420)	(-8.2467)	(-2.2638)	(-1.9455)	(0.2699)
Ret_lag2	-0.0532***	-0.0553***	-0.0025	-0.0537	0.0978
	(-3.3331)	(-3.4564)	(-0.0646)	(-1.0059)	(1.3208)
Ret_lag3	0.0066	0.0066	0.0131	0.0113	0.0808
	(0.4120)	(0.4102)	(0.3406)	(0.2119)	(1.0946)
Ret_lag4	-0.0676***	-0.0678***	0.0172	-0.0351	0.0584
	(-4.2502)	(-4.2564)	(0.4462)	(-0.6617)	(0.7925)
Ret_lag5	-0.0678***	-0.0670***	0.0348	-0.0154	0.0428
	(-4.2827)	(-4.2313)	(0.9119)	(-0.2918)	(0.5851)
Observations	3850	3850	3850	3850	3850
Adj R^2	0.0637	0.0619	0.0359	0.0668	0.1384

Table 4. 3 Correlation Matrix

The table reports Pearson correlation coefficients between the HHC and other risk factors which have explanatory power on stock returns. HHC is the proxy we constructed for the health dimension of human capital. The p-values are reported in parentheses, and ***, **, and * denotes the significance at the 1%, 5%, and 10% levels, respectively.

Correlation Matrix							
	HHC	MKT	SMB	HML	UMD	RMW	CMA
MKT	-0.1183						
	0.1089						
SMB	0.0247	0.4154***					
	0.7386	<.0001					
HML	-0.0008	0.2204***	0.2494***				
	0.9916	0.0026	0.0006				
UMD	0.0206	-0.3419***	-0.18255	-0.4258***			
	0.7806	<.0001	0.0126	<.0001			
RMW	0.1042	-0.4072***	-0.3709***	-0.1170	0.1407*		
	0.1571	<.0001	<.0001	0.1119	0.0554		
CMA	0.0014	-0.0900	0.0698	0.4961***	-0.1292*	0.0325	
	0.9847	0.2231	0.3436	<.0001	0.0787	0.6596	
LIQ	-0.1625**	0.1890***	0.0280	-0.0360	0.0848	-0.0736	-0.0075
	0.0267	0.01	0.7041	0.6258	0.2501	0.3184	0.9195

Table 4. 4 Univariate Portfolios Analysis

For each month, five quantile portfolios are constructed by sorting stocks based on the health-induced human capital (HHC) beta β_{HHC}. HHC betas are obtained by regressing the excess return of individual stocks on the HHC index, controlling for FF3 risk factors. Low portfolio includes stocks with the lowest β_{HHC} and High portfolio consists of stocks with the highest β_{HHC}. The first three columns report the average size, book-to-market ratio, and the HHC beta of individual stocks across five quantile portfolios formed by the HHC betas. Columns 4 reports the average return of each β_{HHC} quantile portfolio and Columns 5-9 present the risk-adjusted returns (alphas), controlling for the following conventional risk factors: market, size, value, momentum, profitability, investment, and liquidity factors. The last row (High-Low) represents the differences of average return and risk-adjusted return between High portfolio and Low portfolio. The t-statistics adjusted by Newey and West (1987) are displayed in parentheses. The symbols ***, **, * indicate statistical significance at 1%, 5%, and 10 % levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HHC Beta Portfolios	Size	BM	Beta	Ret	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	6.94	0.56	-3.00	1.03	-0.02	0.15	0.17	0.15	0.15
				(2.12)	(-0.09)	(0.93)	(1.13)	(1.00)	(1.31)
2	7.58	0.51	-0.96	1.05	0.11	0.24	0.25	0.18	0.19
				(2.57)	(0.84)	(2.87)	(3.60)	(2.18)	(2.71)
3	7.71	0.50	-0.01	1.19	0.25	0.37	0.37	0.31	0.28
				(3.02)	(1.96)	(4.40)	(4.82)	(3.79)	(3.84)
4	7.55	0.51	0.96	1.26	0.29	0.42	0.43	0.36	0.33
				(2.92)	(1.94)	(3.76)	(4.22)	(3.24)	(3.27)
High	6.89	0.52	3.15	1.47	0.46	0.59	0.60	0.54	0.53
				(3.25)	(2.04)	(3.77)	(3.98)	(3.47)	(3.82)
High-Low				0.44*	0.48**	0.45*	0.44*	0.39	0.38*
				(1.95)	(2.03)	(1.78)	(1.72)	(1.65)	(1.91)

Table 4. 5 Portfolios Sorted by HHC Beta Controlling for Firm Characteristics

For each month, five equal-weighted quantile portfolios are formed based on the health-induced human capital (HHC) beta β_{HHC} controlling for other characteristics including size (Panel A), BM (Panel B), momentum (Panel C), and illiquidity (Panel D). HHC betas are obtained by regressing the excess return of individual stocks on the HHC index, controlling for FF3 risk factors. We first sort stocks into five quintile portfolios based on one of the firm characteristics. Within each firm characteristic quintile, we further form five portfolios based on sorting of their HHC betas. All portfolios are balanced monthly. We then calculate the average return across five firm characteristic quantiles for each of five HHC beta portfolios. Low portfolio contains stocks with the lowest β_{HHC} and High portfolio consists of stocks with the highest β_{HHC}. Column one presents the average return for equal-weighted portfolios, and the next five columns report the risk-adjusted returns (alphas) for equal-weighted portfolios, controlling for the following risk factors: market, size, value, momentum, investment, profitability and liquidity, factors. The last row (High-Low) shows the average return and factor-adjusted return differences between High portfolio and Low portfolio. The t-statistics adjusted by Newey and West (1987) are presented in parentheses. The symbols ***, **, * indicate statistical significance at 1%, 5%, and 10 % levels.

Panel A: Controlling for Size

	(1)	(2)	(3)	(4)	(5)	(6)
HHC Beta Portfolios	Average Return	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	1.14	0.09	0.25	0.26	0.23	0.20
	(2.44)	(0.51)	(2.83)	(3.65)	(2.73)	(2.87)
2	1.08	0.13	0.28	0.29	0.22	0.23
	(2.59)	(0.96)	(2.97)	(3.96)	(2.41)	(3.16)
3	1.14	0.19	0.33	0.34	0.27	0.25
	(2.88)	(1.36)	(3.99)	(4.47)	(3.38)	(3.33)
4	1.27	0.30	0.45	0.46	0.41	0.36
	(2.93)	(1.95)	(4.13)	(4.54)	(3.75)	(3.83)
High	1.48	0.46	0.57	0.58	0.51	0.50
	(3.30)	(2.14)	(3.53)	(3.74)	(3.16)	(3.48)
High-Low	0.34**	0.37**	0.33**	0.32**	0.28*	0.30**
	(2.35)	(2.55)	(2.22)	(2.14)	(1.83)	(2.14)

Panel B: Controlling for BM

HHC Beta Portfolios	Average Return	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	1.07	0.03	0.19	0.21	0.19	0.19
	(2.25)	(0.14)	(1.16)	(1.33)	(1.25)	(1.58)
2	1.08	0.13	0.27	0.28	0.20	0.22
	(2.58)	(0.96)	(3.25)	(4.20)	(2.59)	(3.35)
3	1.11	0.17	0.29	0.30	0.22	0.21
	(2.83)	(1.22)	(3.49)	(3.98)	(2.84)	(2.72)
4	1.29	0.31	0.44	0.45	0.38	0.34
	(2.95)	(1.99)	(3.37)	(3.70)	(2.97)	(3.11)
High	1.45	0.43	0.57	0.57	0.52	0.51
	(3.19)	(2.01)	(3.82)	(4.05)	(3.58)	(3.94)

High-Low	0.38*	0.40*	0.38	0.37	0.33	0.32
	(1.68)	(1.68)	(1.47)	(1.44)	(1.38)	(1.62)

Panel C: Controlling for Momentum

HHC Beta Portfolios	Average Return	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	0.97	-0.08	0.08	0.09	0.07	0.10
	(1.99)	(-0.36)	(0.51)	(0.64)	(0.52)	(0.87)
2	1.07	0.12	0.26	0.27	0.21	0.21
	(2.63)	(0.91)	(3.09)	(3.64)	(2.63)	(2.79)
3	1.14	0.19	0.31	0.32	0.24	0.23
	(2.83)	(1.55)	(3.78)	(4.34)	(2.99)	(3.25)
4	1.30	0.32	0.46	0.47	0.40	0.37
	(2.96)	(1.99)	(3.75)	(4.16)	(3.30)	(3.38)
High	1.44	0.44	0.58	0.59	0.52	0.49
	(3.25)	(1.98)	(3.66)	(3.92)	(3.39)	(3.70)
High-Low	0.47**	0.52**	0.51*	0.50*	0.45*	0.38*
	(1.98)	(2.15)	(1.97)	(1.94)	(1.86)	(1.95)

Panel D: Controlling for Illiquidity

HHC Beta Portfolios	Average Return	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	1.12	0.08	0.24	0.25	0.22	0.20
	(2.42)	(0.47)	(2.76)	(3.68)	(2.66)	(2.83)
2	1.01	0.06	0.20	0.21	0.16	0.19
	(2.42)	(0.44)	(2.17)	(2.74)	(1.79)	(2.56)
3	1.15	0.20	0.33	0.34	0.27	0.25
	(2.89)	(1.35)	(3.92)	(4.42)	(3.41)	(3.37)
4	1.26	0.29	0.44	0.45	0.39	0.35
	(2.91)	(1.91)	(3.68)	(4.06)	(3.30)	(3.45)
High	1.49	0.48	0.59	0.60	0.53	0.52
	(3.34)	(2.20)	(3.71)	(3.91)	(3.35)	(3.64)
High-Low	0.37***	0.40***	0.36**	0.35**	0.31**	0.32**
	(2.64)	(2.81)	(2.49)	(2.37)	(2.13)	(2.35)

Table 4. 6 Pricing of Health-induced Human Capital Factor

This table shows the estimating results of second-stage Fama–MacBeth regressions; the coefficient estimates of factors are based on 25 portfolios sorted on market beta (β_{MKT}) and the HHC beta (β_{HHC}). MKT is the excess return on the market portfolio, and HHC is the inverse of *ex ante* health concerns constructed based on the search volume of medical symptoms. SMB and HML are size and value factors from the model of Fama–French (1993), RMW and CMA are Fama-French (2015) profitability and investment factors, UMD is the momentum factor, and LIQ is the aggregate liquidity measure. Newey-West adjusted t-statistics are displayed in parentheses. ***, **, and * indicate the statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	HHC	CAPM+HHC	FF3+ HHC	Carhart4+ HHC	FF5+ HHC	FF5+M+L+ HHC
Constant	1.341***	0.700	0.494	0.394	1.018**	0.778
	(2.91)	(1.59)	(0.87)	(0.72)	(2.41)	(1.09)
HHC	1.072**	0.937**	0.838**	0.810**	0.700**	0.564*
	(2.47)	(2.26)	(2.30)	(2.20)	(2.05)	(1.67)
MKT		0.126	0.508	0.584	0.159	-0.159
		(0.24)	(0.80)	(0.95)	(0.23)	(-0.20)
SMB			-0.003	0.068	0.211	0.394
			(-0.01)	(0.20)	(0.63)	(0.93)
HML			-0.302	-0.253	-0.698	-0.760
			(-0.44)	(-0.36)	(-1.14))	(-1.41)
UMD				0.103		0.416
				(0.14)		(0.62)
RMW					1.020*	1.180**
					(1.80)	(2.41)
CMA					-0.471*	-0.550*
					(-1.69)	(-1.94)
LIQ						-2.602
						(-1.23)
Adj R^2	0.025	0.396	0.341	0.356	0.357	0.381

Table 4. 7 Robustness: Univariate Portfolios Analysis

To address the forward looking bias caused by winsorization, we run a robustness test and develop the health index without winsorizing the data. For each month, we sort stocks into five quantile portfolios based on the health-induced human capital (HHC) beta β_{HHC}. HHC betas are obtained by regressing the excess return of individual stocks on the HHC index, controlling for FF3 risk factors. Low portfolio includes stocks with the lowest β_{HHC} and High portfolio contains stocks with the highest β_{HHC}. Columns 1 reports the average return of each β_{HHC} quantile portfolio and Columns 2-6 present the risk-adjusted returns (alphas), controlling for the following conventional risk factors: market, size, value, momentum, profitability, investment, and liquidity factors. The last row (High-Low) represents the return differences between High portfolio and Low portfolio. The t-statistics adjusted by Newey and West (1987) are presented in parentheses, and ***, **, and * denote the statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
HHC Beta Portfolios	Average Return	CAPM Alpha	FF3 Alpha	Carhart4 Alpha	FF5 Alpha	FF5+ML Alpha
Low	1.07	0.03	0.17	0.19	0.16	0.18
	(2.29)	(0.11)	(1.07)	(1.26)	(1.09)	(1.55)
2	1.18	0.24	0.36	0.37	0.31	0.31
	(2.84)	(1.79)	(4.85)	(5.74)	(3.91)	(4.36)
3	1.14	0.21	0.32	0.33	0.26	0.23
	(2.87)	(1.66)	(4.18)	(4.97)	(3.56)	(3.89)
4	1.20	0.24	0.36	0.37	0.30	0.28
	(2.77)	(1.44)	(2.61)	(2.77)	(2.25)	(2.43)
High	1.42	0.38	0.56	0.57	0.51	0.49
	(3.08)	(1.71)	(3.86)	(4.39)	(3.84)	(3.93)
High-Low	0.35*	0.36*	0.39*	0.38*	0.35	0.31*
	(1.71)	(1.67)	(1.72)	(1.72)	(1.64)	(1.77)

5. General Conclusion

This thesis contains three essays and all three essays make significant contributions to asset pricing and behavior finance literature. The first essay, we contribute to the literature by incorporating social and environmental risks in a CAPM-based model. Our theoretical model implies that the uncertainty related to social and environmental costs alters the stock's systematic risk, and two additional risk premia are demanded to compensate higher CSR risk in the market. To empirically test the spirit of our theory, we first estimate aggregate market level traded social and environmental factors using the sample data from MSCI ESG and equity returns. The empirical analysis provides consistent evidence to the implication of our theoretical model. Specifically, investors demand extra premium to hold assets with negative social and environmental factor loadings. In addition, we demonstrate that portfolio exposure with respect to social and environmental factors are both cross-sectionally priced.

The second essay, we contribute to the literature by linking human moral characteristics to financial decisions that have an ethical component. Our experimental studies allow us to study the role of moral identity in a financial investment context. In addition, we discover the moderating effects of financial incentive and physical distance on the relation between moral identity and unethical investment. Specifically, individuals with lower moral identity are incentivized to invest in immoral portfolio only when they perceive themselves to be physically distant to the immoral company. Finally, our findings interpret the scope insensitivity phenomenon in the financial domain and provide consistent evidence that physical proximity triggers this phenomenon, in returns individuals with lower moral identity are less sensitive to financial incentives, thus the WTI in immoral portfolio is lower.

In the third essay, our contribution to the human capital literature is threefold. First, we develop a health index which illustrates *ex ante* human health perceptions by using Google Trends internet searching on medical concerns. Second, we examine the impact of our health perspective human capital on equity market and address the lack of research on the impact of human health as an important component of human capital on asset prices.

Third, we discover a positive and significant price premium on human capital in terms of the perception of health conditions.

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