The Journal of FINANCE
The Journal of THE AMERICAN FINANCE ASSOCIATION

THE JOURNAL OF FINANCE • VOL. LXXIV, NO. 4 • AUGUST 2019

Income Hedging, Dynamic Style Preferences, and Return Predictability

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ABSTRACT

We propose a theoretical measure of income hedging demand and show that it affects asset prices. We focus on the value factor and first demonstrate that our demand estimates are correlated with the actual demands of retail and mutual fund investors. We then show that the aggregate high-minus-low (HML) demand predicts HML returns. Exploiting the state-level variation in income risk, we demonstrate that state-level hedging demands predict state-level HML returns. A long-short portfolio that exploits this hedging-induced predictability earns an annualized risk-adjusted return of 6%.

INCOME RISK IS A FUNDAMENTAL source of uncertainty that households face, and hence it should affect their financial decisions. Several recent studies demonstrate that income risk influences the portfolio decisions of U.S. and European households. For example, Angerer and Lam (2009) demonstrate that U.S. households with higher permanent income risk invest less in risky assets. Betermier et al. (2012) show that the financial decisions of Swedish households are sensitive to wage volatility.

A related literature provides household-level evidence that portfolio decisions are affected by income hedging considerations. Bonaparte, Korniotis, and Kumar (2014) find evidence of income hedging in the decisions of Dutch and U.S. households. They show that households whose income growth is highly correlated with market returns participate less in the market and allocate less of their wealth to risky assets. Using Swedish data, Betermier, Calvet, and Sodini (2017) argue that the tilt of some investors toward value versus growth stocks is motivated by income hedging concerns. They show that income

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DOI: 10.1111/jofi.12775

hedging considerations are strongest for those households with high human capital and high exposure to aggregate risk.[1] Korniotis and Kumar (2011) further demonstrate that certain types of financial assets facilitate income smoothing and improve risk sharing across U.S. states.

Motivated by the household-level evidence on income hedging, in this paper, we examine its potential asset pricing implications. In particular, we investigate the potential link between the aggregate income hedging behavior of U.S. households and the predictability in stock returns. Our primary conjecture is that the demand for financial assets that facilitate income hedging varies as their hedging potential changes over time. If such hedging-induced demand shifts are systematic, they could affect prices. This conjecture is partially motivated by dynamic portfolio choice models, which demonstrate that when investment opportunities are time-varying, investors should rebalance their portfolios as they learn about future investment opportunities (e.g., Campbell and Viceira (1999), Campbell and Vuolteenaho (2004), and Jurek and Viceira (2011)).

We connect this basic prediction of dynamic portfolio choice models with the literature on style investing, which shows that investors systematically move in and out of certain investment styles (e.g., Barberis and Shleifer (2003), Kumar (2009), and Wahal and Yavuz (2013)). We argue that style shifts between value and growth stocks might be motivated in part by the time-variation in income hedging opportunities. Such systematic demand shifts could generate predictable variation in the returns of value and growth portfolios.

We formalize this economic insight in a model that combines the noise trader specification of De Long et al. (1990), the Bayesian framework of Barberis (2000), and the income hedging model of Viceira (2001). In the model, there are two groups of investors. The first group comprises workers, who receive stochastic income and are concerned about income risk. The second group is the sophisticated investors, who are risk neutral and face transaction costs. We solve the model analytically, and obtain explicit solutions for the optimal portfolios of workers and sophisticated investors. Similar to Viceira (2001), asset demands by workers include an income hedging term, which depends on the covariances between asset returns and income, scaled by the covariance matrix of asset returns. This covariance-based term is our proposed measure of income hedging demand (IHD).

When the conditional covariance between income and an asset decreases, the income hedging potential of this asset increases and the IHD measure increases. Workers then demand more of the asset, creating price pressure, which in our model cannot be fully absorbed by the sophisticated investors due to transaction costs. This price pressure today generates lower returns in the future. Overall, the key theoretical prediction is that there is a *negative* relation between our IHD measure and future asset returns.

[1] Other papers related to income hedging include Heaton and Lucas (2000), Viceira (2001), and Vissing-Jorgensen (2002).

To test our predictability hypothesis, we focus on the value factor or the high-minus-low (HML) style portfolio. We focus on the HML factor because existing literature suggests that income risk affects the choice between value and growth stocks. For example, studies using aggregate data find that the value premium is related to income hedging. In particular, Koijen, Lustig, and Nieuwerburgh (2017) show that value stocks are especially risky because their cash flows are low during deep recessions, that is, during periods when aggregate income growth is very negative. Thus, investors could hedge against this risk by investing in growth stocks.

Betermier, Calvet, and Sodini (2017) provide direct evidence of income hedging using household-level data. They find that households with high income risk or high human capital and households employed in highly cyclical sectors avoid value stocks and prefer growth stocks. Cronqvist, Siegel, and Yu (2015) also find that value versus growth investing is one of the most predominant investment styles. Further, they show that households with higher human capital (i.e., high labor income and high education) tend to prefer growth stocks. Moreover, investors with more procyclical income (i.e., high correlation between labor income growth and GDP growth) also tend to prefer growth stocks.

We also focus on the HML portfolio because it satisfies the necessary conditions required to generate predictability in returns. First, value and growth investment styles have been popular as far back as the 1930s (e.g., Graham and Dodd (1934)). Further, the average investor can easily gain exposure to value and growth portfolios (Wahal and Yavuz (2013)). Jurek and Viceira (2011) report that in the universe of mutual funds in the Center for Research in Security Prices (CRSP) database, about 78% of funds can be categorized as either value or growth funds. Second, the income hedging potential of the HML portfolio varies significantly over time, which generates time-varying demand shifts that can potentially influence stock prices.

Since hedging-induced investments cannot be directly observed, we estimate the IHD using the relation predicted by our model. Because we want to examine the aggregate asset pricing implications of income hedging, we construct the IHD using aggregate U.S. and state-level income data. Specifically, we adopt a conditional estimation approach where we compute variances and covariances using a 10-year rolling window. Using these conditional moment estimates we compute IHD at both the U.S. state level and the national level. As shown in Figure 1, the IHD estimates exhibit substantial variation in the cross section and over time. For instance, in every period some U.S. states have negative while others have positive IHD estimates.

Before using our IHD measure to predict asset returns, we investigate whether these theoretical demand estimates are related to actual investor demands for value and growth stocks. We perform two validation tests. In the first test, we compute the relative portfolio weights in value and growth stocks based on the actual stock holdings of a sample of retail investors. We find that the correlation between the actual relative weight and our IHD measure is positive and statistically significant.

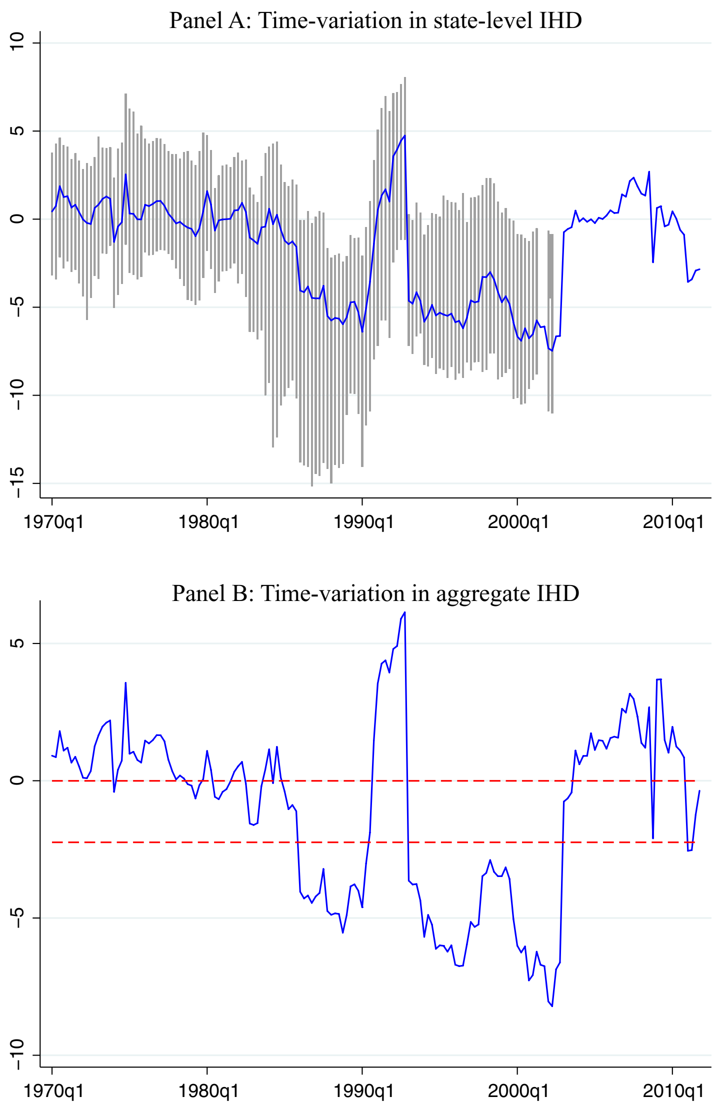

Figure 1. Time-variation in income hedging demand (IHD). This figure displays the time series of IHD. Panel A displays the time series of the average state-level IHD (dark line) over the sample period. We also show the range spikes extending from the 10^{th} to the 90^{th} percentile of the cross-sectional distribution of the state-level IHD each year (light vertical lines). The state-level IHD is based on scaled conditional covariances between state-level income and HML, and then averaged each quarter across states, weighting each state by the fraction of national financial wealth held by state residents (calculated using IRS data on capital gains and dividend income). Conditional covariances are calculated as the covariance between changes in quarterly state-level real income per-capita and HML returns over the past 40 quarters for each quarter during the sample period with 40 trailing observations. In Panel B, IHD is based on conditional covariances between changes in quarterly U.S. real income per-capita and HML returns over the past 40 quarters for each quarter during the sample period with 40 trailing observations. Also shown in Panel B are the two-standard-error bands around the sample mean of the IHD (dashed lines). The sample period is from Q1 1970 to Q4 2011. (Color figure can be viewed at wileyonlinelibrary.com)

In the second validation test, we use mutual fund data from CRSP. Consistent with our model, we find that the average net flows into value funds are positively correlated with our IHD measure. In contrast, the average net flows into growth funds are negatively correlated with our IHD measure. These findings suggest that the theoretical covariance-based demand measures capture the portfolio decisions of actual market participants reasonably well.

In our asset pricing tests, we first focus on aggregate U.S. income risk and show that our U.S.-level IHD estimates can predict HML portfolio returns. We find that high IHD is associated with low HML returns in the next period. In economic terms, a one-standard-deviation increase in the IHD is associated with 0.59% lower HML return next month and 0.96% lower HML return next quarter. The evidence of predictability remains significant for about a year, suggesting that shifts in hedging-induced demand have a medium-term impact on asset prices. These findings are robust to a number of control variables, and they are not driven by macroeconomic shocks or estimation biases.

Next, we examine the implications of income hedging for asset prices across U.S. states. Consistent with our previous evidence, we find that state-level IHD estimates can predict state-level HML returns, especially among stocks with high local ownership. In contrast, among stocks with low local ownership, evidence of hedging-induced return predictability is weak. A long-short portfolio that exploits hedging-induced predictability in the cross section of U.S. states earns an annualized risk-adjusted return of over 6%. This evidence suggests that at least part of the HML predictability at the U.S. state level is induced by geographical heterogeneity in income risk.

We complement our main results with a set of tests designed to show that our main findings are related to income hedging. First, we follow Davis and Willen (2000), who show that across 10 occupation categories, electrical engineers face the highest income risk and auto mechanics face the lowest. Given their findings, we expect the IHD of electrical engineers, who have the most to gain from income hedging, to more closely replicate our main result than that of auto mechanics, who are unlikely to exhibit income hedging behavior. Consistent with this conjecture, we find that the electrical engineers' IHD measure is a statistically significant predictor of HML returns. In contrast, auto mechanics' IHD is an insignificant predictor of HML returns.

Second, Guvenen et al. (2017) suggest that income hedging motives vary across households due to cross-sectional differences in the exposure to aggregate risk. They show that those at the very bottom and very top of the income distribution are the ones who bear income risk both with respect to aggregate GDP and their employer's earnings. Since most market participants are at the top of the income distribution (Campbell et al. (2016)), the findings in Guvenen et al. (2017) suggest that the IHD of the top earners should have the most predictive power for returns. Consistent with this view, we find that the most important IHD predictors are those calculated using income growth for the 96% to 99% and top 1% of households.

Collectively, our findings contribute to the literature on household portfolio choice and income hedging (e.g., Samuelson (1969), Merton (1969, 1971, 1973), Viceira (2001)). Specifically, we propose a measure of aggregate IHD, which we validate using data on retail investors and mutual fund flows. Our measure is theoretically motivated by a structural model with two types of investors (workers and sophisticated investors), which we solve analytically.

Further, our paper contributes to the literature on style investing. Barberis and Shleifer (2003) posit that investors' grouping of assets into broad styles can help explain excess comovement within style categories (Lee, Shleifer, and Thaler (1991), Barberis, Shleifer, and Wurgler (2005)). Teo and Woo (2004) demonstrate that style investing is related to momentum and reversal patterns. Kumar (2009) and Campbell, Ramadorai, and Ranish (2014) document style-switching behavior among retail investors. Kumar (2009) shows that style-switching behavior has an effect on stock returns.

More recently, Wahal and Yavuz (2013) show that past style returns are significant predictors of future returns for individual stocks categorized into styles. Specifically, they test whether style investing leads to return predictability by examining whether past style returns have any predictive power in the cross section. Similar to our empirical framework, they identify styles using size and book-to-market portfolios. However, they directly test their conjecture using Fama and MacBeth (1973) regressions of future stock returns on size, book-to-market, past stock returns, and past style returns. Compared to Wahal and Yavuz (2013), our starting point is an economic model in which IHD is a predictor of returns.

Overall, we connect the literatures on style investing and income hedging, and show that a driver of the style-switching activities of investors is likely to be their income hedging motives. Specifically, we show that income hedging generates systematic shifts in demand across style portfolios and can predict future style returns. This income-hedging-induced predictability mechanism is novel and has not been studied by existing asset pricing literature on human capital (e.g., Fama and Schwert (1977b), Campbell (1996), Jagannathan and Wang (1996), Campbell et al. (2016)).

Our work also complements recent literature on how firms insure workers through their labor contracts, which can affect asset prices (Berk and Walden (2013), Marfè (2017)). We complement this work and argue that both hedging via labor contracts and financial markets can coexist. Guvenen et al. (2017) show that those at the very bottom and very top of the income distribution are the ones who bear income risk. In contrast, workers in the middle of the income distribution are more likely to be insured by their employers, and hence do not bear much income risk. Consistent with this view, we show that our results are largely driven by the income risk of those at the top, and not the middle, of the income distribution.

Further, we present two tests suggesting that hedging via financial markets and labor contracts are likely to be complementary channels. First, we split U.S. states into those with high unionization and low unionization rates. Since unions typically advocate for rigid wage contracts (e.g., Shister (1943)), workers in areas with higher unionization rates should have a weaker motivation to self-insure in financial markets. We find that our results hold in both subsamples.

In our second test, we compute the labor share measure of Marfè (2017) and include it as an additional control variable in our national-level HML predictive regressions. We find that IHD remains an economically and statistically significant HML predictor in the presence of the labor share measure.

The rest of the paper is organized as follows. Section I discusses a model with time-varying IHDs. Section II describes our method for estimating hedging demand and provides estimates of IHDs. Section III presents validation tests comparing IHD estimates with actual time-variation in demand for value and growth stocks. Section V provides evidence of return predictability at the aggregate level and Section V extends the predictability analysis to the state level. Section VI includes results from additional analyses as well as robustness tests. Finally, Section VII concludes with a brief discussion.

I. A Two-Investor Model with Income Hedging

Our empirical analysis is based on a model that describes how time-variation in the income hedging potential of financial assets can generate predictability in asset returns. The model generates a theoretically motivated measure of income hedging, and highlights the conditions under which this measure should be related to future asset returns.

Our model extends the noise trader specification of De Long et al. (1990) to account for Bayesian learning as in Barberis (2000) and income hedging as in Viceira (2001). We follow this approach because most of the literature that seeks to explain return predictability uses the two-investor setup of De Long et al. with Bayesian learning. See, for example, Timmermann (1993, 1996), Lewellen and Shanken (2002), and Pastor and Veronesi (2009). The main purpose of our model is to provide a formal way for studying the relation between return predictability and income hedging.[2]

For our theoretical framework, we consider a closed endowment economy as in De Long et al. (1990). In this economy, there is a risk-free asset. Its supply is perfectly elastic and its price is fixed at one. The riskless asset pays interest $r_f, t+1$, which is constant and positive ($r_{f,t+1} = r_f > 0$). The n risky assets of the economy are in limited fixed supply. The fixed supply of risky assets is denoted by the $n \times 1$ vector $\bar{\boldsymbol{N}}$. The vector $\boldsymbol{p}_t$ is the vector of prices for the risky assets, and $\boldsymbol{d}_t$ is the vector of dividends paid by the risky assets. For simplicity, we assume that dividends are i.i.d. with mean $\bar{\boldsymbol{d}}$ and covariance matrix $\boldsymbol{\Sigma}_d$. The vector $\boldsymbol{r}^x_{t+1}$ denotes cum-dividend returns in excess of the risk-free rate and is equal to $\boldsymbol{p}_{t+1} + \boldsymbol{d}_{t+1} - (1 + r_f)\boldsymbol{p}_t$. Finally, $\boldsymbol{\mu}_{r,t} = \mathbb{E}_t[\boldsymbol{r}^x_{t+1}]$ is the vector of risk premia, and the matrix $\boldsymbol{\Sigma}_{r,t} = Var_t(\boldsymbol{r}^x_{t+1})$ is the conditional covariance matrix of cum-dividend returns.

The economy is populated by overlapping generations of investors who live for two periods. There are two types of investors: workers and sophisticated

[2] Our model is related to existing work on the relation between human capital and asset returns. For example, see Campbell (1996), Jagannathan and Wang (1996), and Campbell et al. (2016). None of these studies examine return predictability, which is our focus.

investors, with population masses ν and $1-\nu$, respectively ($\nu \in (0, 1)$). In the first period, both types of investors receive exogenous endowments that can be invested in the risky and risk-free assets. There is no consumption in the first period. In the second period, investors receive dividends, sell their investments, consume all of their wealth, and die.

Sophisticated investors are risk-neutral. They have complete information and are characterized by rational expectations. In the first period, sophisticated investors pay quadratic transaction costs for investing in risky assets as in Gârleanu and Pedersen (2013). These costs are a dead-weight loss to the economy and proxy for limited external capital. The transaction costs are summarized by a diagonal matrix $\boldsymbol{Q}$. For simplicity, we assume that $\boldsymbol{Q}$ is equal to $(q/2) \times \boldsymbol{I}$, where q is a positive scalar and $\boldsymbol{I}$ is the identity matrix.[3]

Workers are characterized by quadratic utility with identical risk aversion parameters γ ($\gamma > 0$). In addition to their first-period endowment (y_t), during the second period workers receive another stochastic endowment (income), which is denoted by y_{t+1}. The dynamics of income are the same for all workers and across generations. Income dynamics are described by the following process with time-varying volatility:

$$y_{t+1} = y_t + \mu_y + \sigma_{y,t} e_{y,t+1}. \tag{1}$$

The constant μ_y denotes expected income changes, and $e_{y,t+1}$ are i.i.d. normal shocks with zero mean and unit variance. The parameter $\sigma_{y,t}$ captures the time-variation in income volatility. This parameter is orthogonal to all other shocks in the economy. To ensure that the time-varying volatility is always positive, we assume that $\sigma_{y,t}$ follows an i.i.d. inverse-gamma distribution $IG(\xi, \mu_{\sigma_y}(\xi - 1))$ with $\xi > 2$ and $\mu_{\sigma_y} > 0$. The income process in equation (1) is quite standard in the consumption and income hedging literatures (e.g., Mankiw and Shapiro (1985)). The only difference relative to existing models is that we assume income heteroscedasticity with time-varying volatility. Moreover, following Viceira (2001), we assume that markets are incomplete. Therefore, the income risk of workers described in equation (1) cannot be perfectly hedged by the traded assets. However, asset returns and workers' income are conditionally correlated with $\boldsymbol{\Sigma}_{y,r,t}$, the $n \times 1$ vector of conditional covariances between asset returns and income in first-differences.[4]

Moreover, we assume that workers are less informed than the sophisticated investors. Specifically, as in Barberis (2000), workers infer return and income

[3] Technically, the presence of transaction costs guarantees that the demand of the risk-neutral sophisticated investors is finite.

[4] We remain agnostic as to why labor income and asset returns are correlated. Campbell et al. (2016) discuss this issue in relation to HML factor returns. They show that income growth of the top 1% of the income distribution is a priced factor that is related to the HML factor. They conjecture that high-income investors may be disproportionately employed by value rather than by growth firms. Using data from Compustat, they find that their high-income factor covaries more with the per-employee wage growth of value firms than with the wage growth of growth firms. This intuition can apply in part to our setting as well since we find that the IHD of the top 1% of the income distribution can predict the HML return. See Section VI.B.

moments using Bayes's rule with uninformative priors. Although workers live only for two periods, they observe a history of T observations for income and asset prices. To derive closed-form solutions for asset demands, we also assume that workers believe that asset returns *and* income changes are jointly normally distributed i.i.d. variables with unknown mean and volatility.

Finally, workers do not observe the demand of sophisticated investors, whereas sophisticated investors are fully aware of workers' decisions. This assumption is reasonable because sophisticated investors represent market makers and brokers, who in practice observe the limit order flow and can infer investors' decisions. Sophisticated investors can also be institutional investors and hedge fund managers who have more resources and better information. In contrast, it is reasonable to assume that workers, who represent the average retail investor, have access only to public information (like the history of asset prices) and generally have less resources to infer the decisions of institutional investors and form expectations.[5]

A. Market-Clearing: Hedging and Asset Prices

Based on the above assumptions, we can derive the market-clearing condition.

PROPOSITION 1: *The market-clearing condition for our model economy is given by*

$$\bar{\boldsymbol{N}} = \frac{1-\nu}{q(1+r_f)}\mathbb{E}_t^{so}[\boldsymbol{r}_{t+1}^x] + \frac{\nu(T-n-3)}{\gamma(T+1)}\widehat{\boldsymbol{\Sigma}}_{r,t}^{-1}\widehat{\boldsymbol{\mu}}_{r,t} + \nu IHD_t. \tag{2}$$

PROOF: See the Appendix. ■

The market-clearing condition (2) depends on three terms. The first is the vector of expected excess returns based on sophisticated investors' rational beliefs ($\mathbb{E}_t^{so}[]$), which reflect complete information. When expected excess returns are high, sophisticated investors demand more of the risky assets. The second term captures the traditional risk-return trade-off based on workers' estimates of risk premia ($\widehat{\boldsymbol{\mu}}_{r,t}$) and asset variances ($\widehat{\boldsymbol{\Sigma}}_{r,t}$). When workers estimate high risk-return ratios, they demand more of the risky assets. The term $(T-n-3)/(T+1)$ is an adjustment to the risk-return ratio because workers are Bayesian optimizers with uninformative priors.[6] This term accounts for parameter uncertainty.

The third term in equation (2) is workers' estimated IHD. The IHD term is the *negative* value of the estimated covariances of asset returns and income

[5] There can be multiple groups of sophisticated investors. For tractability, we avoid introducing more than two types of investors, which is consistent with many existing models.

[6] T is the number of time-series observations that workers use to estimate return and income moments and n is the number of assets.

changes scaled by the estimated asset variances:

$$IHD_t = -\widehat{\boldsymbol{\Sigma}}_{r,t}^{-1}\widehat{\boldsymbol{\Sigma}}_{y,r,t}. \tag{3}$$

When the covariances between asset returns and income in first-differences decrease, the income hedging potential of financial assets increases. Consequently, workers demand more of the risky assets. In contrast, when the estimated covariances between asset returns and income in first-differences increase, the income hedging potential of financial assets decreases. In this case, workers demand less of the risky assets.[7]

B. Empirical Predictions: Hedging and Return Predictability

We rearrange the market-clearing condition (2) in terms of sophisticated investors' expected returns and obtain the following expression:

$$\mathbb{E}_t^{so}[\boldsymbol{r}_{t+1}^x] = \frac{q(1+r_f)}{1-\nu}\bar{\boldsymbol{N}} - \frac{\nu q(1+r_f)}{1-\nu}\frac{T-n-3}{\gamma(T+1)}\widehat{\boldsymbol{\Sigma}}_{r,t}^{-1}\widehat{\boldsymbol{\mu}}_{r,t} - \frac{\nu q(1+r_f)}{1-\nu}IHD_t. \tag{4}$$

Since sophisticated investors have rational expectations, we can replace the expectation operator in equation (4) with an error term $\boldsymbol{\epsilon}_{t+1}$, to conclude that

$$\boldsymbol{r}_{t+1}^x = \frac{q(1+r_f)}{1-\nu}\bar{\boldsymbol{N}} - \frac{\nu q(1+r_f)}{1-\nu}\frac{T-n-3}{\gamma(T+1)}\widehat{\boldsymbol{\Sigma}}_{r,t}^{-1}\widehat{\boldsymbol{\mu}}_{r,t} - \frac{\nu q(1+r_f)}{1-\nu}IHD_t + \boldsymbol{\epsilon}_{t+1}. \tag{5}$$

Equation (5) makes a clear empirical prediction. It implies that changes in hedging demand lead to predictable patterns in returns. Specifically, when the income hedging potential of financial assets increases, IHD will also increase, and equation (5) suggests that future returns will be lower. Equation (5) also predicts a negative relationship between the term $\widehat{\boldsymbol{\Sigma}}_{r,t}^{-1}\widehat{\boldsymbol{\mu}}_{r,t}$ and future returns. We call this term the RISK-RETURN term and include it in our estimation for completeness.

Equation (5) clarifies the conditions under which income hedging can lead to return predictability. First, the effect of income hedging on returns depends on the magnitude of the transaction costs q, which proxies for costly capital. A large q implies that the effect of income hedging on returns is strong because

[7] In the model, time-variation in IHD, and thus predictability in returns, arises because workers are Bayesian updaters who use past observations to estimate asset pricing moments. Hence, the market-clearing condition in equation (2) implies a high-order, nonlinear recursion for the pricing function, which does not have a closed-form solution. The nontractability of the pricing function is due to Bayesian updating by workers. We can obtain an explicit solution for the pricing function for a limiting case. Specifically, in Section I of the Internet Appendix, we assume that workers have complete information. In this case, time-variation in IHD is due to time-variation in income volatility. The complete information model of the Internet Appendix is very similar to that of De Long et al. (1990), with the exception that, instead of noise traders, we consider income earners who optimally hedge income risk. The Internet Appendix may be found in the online version of this article.

sophisticated investors cannot trade easily due to high transaction costs. Second, the effect of income hedging on returns depends on the relative population masses of workers and sophisticated investors, that is, ν and $1 - \nu$, respectively. In particular, the effect of income hedging strengthens when there is a large number of workers and a small number of sophisticated investors in the economy. In sum, as long as investing in risky assets is costly and there is a positive mass of workers, shifts in workers' asset demands can generate predictability in asset returns.

C. Simulation Evidence and the Income Hedging Mechanism

Before estimating equation (5), we provide simulation evidence showing that for reasonable model parameters, the predictability generated by the model matches the predictability we document in our empirical tests. This is an important exercise that lends credence to our conjecture that the observed predictability is related to income hedging.

In particular, in Section II of the Internet Appendix, we simulate expected HML returns ($\mathbb{E}_t[\boldsymbol{r}_{t+1}^{HML}]$) for our two-investor model using the observed IHD measure and the market-clearing condition from equation (2). The simulation exercise shows that when we calibrate the deep economic parameters in equation (2) to match the findings in previous literature ($r_f = 1.26\%$, $\nu = 0.4$, $q = 0.4\%$, $\gamma = 13$) and the structure of our empirical design ($T = 40$, $n = 4$), the observed IHD is able to generate the HML return predictability we see in the data. These results are reported in Table IA.I of the Internet Appendix.

II. IHD of Financial Assets

Our empirical analysis is based on the following key implication of our model: If the hedging potential of financial assets is time-varying, then IHD should also be time-varying, which can generate predictable patterns in asset returns. In this section, we examine whether there is time-variation in the income hedging potential of the value factor. We focus on the value factor for a variety of reasons, as explained in Section II.A. We also use aggregate income data because we want to measure the systematic effects of income hedging that arise at the aggregate market level.

A. Choice of HML as an Income Hedging Instrument

To operationalize our conjecture that changes in hedging demand can generate predictable patterns in stock returns, we need to identify portfolios that have substantial income hedging potential. In addition, to identify predictability in realized portfolio returns, it is necessary to focus on investment strategies that are well known and accessible to investors (e.g., Wahal and Yavuz (2013)). We focus on the value factor, or the HML portfolio, because it satisfies both of these requirements.

To begin, the value effect has been documented as far back as the 1930s (e.g., Graham and Dodd (1934)). Also, as we see in Figure 1, the IHD of HML varies considerably over time. Further, the pervasive nature of value and growth suggests that investors can adopt these investment styles easily. For example, Jurek and Viceira (2011) report that in the universe of mutual funds in the CRSP database, about 78% of funds can be categorized as either value or growth funds.

Existing literature has also documented that income risk affects the choice between value and growth stocks. In particular, there is ample evidence that the HML premium is compensation for risk related to aggregate income.[8] More recently, Koijen, Lustig, and Nieuwerburgh (2017) provide explicit evidence that value stocks are especially risky because their cash flows are low during deep recessions, that is, during periods when aggregate income growth is very negative. Thus, investors could hedge against this risk by investing in growth stocks. Overall, studies that use aggregate data find evidence consistent with the value premium being related to income hedging.

Betermier, Calvet, and Sodini (2017) use household-level data and provide direct evidence of income hedging. They find that households with high income risk or high human capital and households that are employed in highly cyclical sectors avoid value stocks and prefer growth stocks. They offer various explanations as to why the level of human capital in particular should affect the preference of value versus growth stocks. They argue that in production of asset pricing models (e.g., Berk, Green, and Naiko (1999), Zhang (2004)), human and physical capital are complementary factors of production. Thus, owners of high human capital should hedge income risk by not investing in firms with high physical capital, which tend to be value firms.

Similar to Betermier, Calvet, and Sodini (2017), Cronqvist, Siegel, and Yu (2015) show that value versus growth investing is a predominant investment style. These authors provide evidence of a genetic component to the preference of value and growth stocks. They also show that households with higher human capital (i.e., high labor income and high education) tend to prefer growth stocks. Moreover, investors with more procyclical income (i.e., a high correlation between labor income growth and GDP growth) also tend to prefer growth stocks.

A related literature offers another explanation as to why there might be a relation between income risk and the HML factor. Specifically, Kogan et al. (2017) build a production model based on the evidence that innovation at the firm level is an important determinant of future growth (Kogan, Papanikolaou, and Stoffman (2017)). In the model, firms that develop new technologies and innovate are growth firms, and the remaining firms are value firms. More importantly, the rents from innovation accrue to very few agents, while the rest of the population is exposed to creative destruction or displacement risk

[8] See Jagannathan and Wang (1996), Campbell (1996), Jagannathan, Kubota, and Takehara (1998), Lettau and Ludvigson (2001b), Lustig and Nieuwerburgh (2005), Petkova and Zhang (2005), Santos and Veronesi (2006), and Yogo (2006).

(e.g., Garleânu, Kogan, and Panageas (2012)). The assumption that only a few agents benefit from innovation is supported by evidence from patents, which is the main empirical proxy for innovation. For instance, Acemoglu, Akcigit, and Celik (2014) note that only a small fraction of all patents filed are highly cited, with the rest receiving almost no citations and creating almost no value for the patent owner.

Because of displacement risk, the majority of investors should tilt their portfolios to growth stocks "as a hedge against the potential wealth reallocation that may result from future technological innovation" (Kogan et al. (2017), p. 2). Within our context, investors have greater desire to invest in growth stocks when the correlation between their income growth and returns to growth stocks is especially low. These low correlations can signal that their income and the future potential of growth firms may be diverging, and thus they need to increase their holdings of growth stocks even further.

B. Data and Summary Statistics

In this section, we provide a brief description of our data sources and present summary statistics for our main variables.

B.1. Aggregate Income Risk and the HML Factor

We obtain HML returns from Ken French's data library, and quarterly U.S. income data from the Bureau of Economic Analysis (BEA).[9] The sample period is from Q1 1960 to Q4 2011. The summary statistics reported at the top of Table I demonstrate that HML returns are positive on average and highly volatile. Specifically, the quarterly mean and standard deviation of the value factor are 1.247% and 6.192%, respectively.

B.2. State-Level Income Risk

In addition to the aggregate income hedging motive, we consider income hedging at the state level. We explore state-level income hedging because income shocks are not diversifiable. As a result, the income risk relevant for asset prices need not be the national income risk, but rather more disaggregated measures of risk (e.g., Constantinides and Duffie (1996)). Our choice is also motivated by evidence in Korniotis (2008) and Korniotis and Kumar (2013) that state-level income shocks are systematic. To compute the state-level IHD measure, we use state income data from the Bureau of Labor Statistics (BLS).

[9] Income is the BEA's personal income measure, which is the sum of wages and salaries, proprietors' income, and personal current transfer receipts less contributions for government social insurance. Our measure of income excludes income from investments (i.e., interest and dividends).

Table I

Summary Statistics

This table reports summary statistics of quarterly HML returns and state-level HML returns over the sample period. State-level HML returns are calculated as the return from a value-weighted portfolio of stocks headquartered in a given state that goes long (short) in the stocks of firms with a book-to-market ratio in the highest (lowest) within-state quartile. We consider states with at least 30 firms headquartered in the state during a given quarter. The sample period is from Q1 1960 to Q4 2011.

Variable	Mean	Median	Std. Dev.	10th pctile	90th pctile
HML Portfolio Return	1.247	0.590	6.192	−4.956	9.770
State HML Returns					
AR	−6.556	−6.556	10.437	−13.936	0.824
AZ	0.674	1.105	9.170	−9.837	10.877
CA	0.615	0.017	7.302	−8.651	9.227
CO	1.939	1.141	9.529	−7.563	12.829
CT	0.926	0.108	6.678	−6.520	8.447
FL	2.226	1.395	6.660	−4.931	10.650
GA	1.910	1.343	7.592	−6.277	11.465
IA	−1.146	−1.218	7.301	−9.508	7.721
IL	−0.057	−0.788	4.821	−5.556	6.484
IN	0.317	−0.111	8.217	−7.675	8.962
KS	1.591	1.753	9.951	−7.754	13.175
KY	0.751	1.560	10.335	−10.820	13.755
LA	0.976	0.104	12.040	−10.032	9.353
MA	0.606	0.163	8.052	−9.429	11.567
MD	1.483	0.809	8.144	−8.762	9.977
MI	1.045	0.069	11.067	−8.490	11.720
MN	1.219	0.934	7.261	−6.302	8.337
MO	1.477	0.964	7.900	−7.319	11.589
NC	1.142	0.686	8.191	−6.899	9.335
NH	3.028	2.409	8.684	−6.924	15.099
NJ	0.975	−0.151	9.634	−7.969	9.274
NV	0.737	1.409	11.139	−16.182	12.815
NY	0.878	0.671	6.854	−5.800	7.251
OH	0.635	−0.223	6.297	−5.643	6.764
OK	1.858	1.835	10.898	−12.046	14.701
OR	1.133	0.761	11.034	−13.738	14.202
PA	1.241	0.330	6.709	−6.563	9.234
SC	0.760	0.238	8.832	−10.691	9.986
TN	2.531	1.374	10.361	−6.798	10.984
TX	1.240	1.096	5.570	−4.960	7.224
UT	0.814	1.046	12.136	−12.086	14.681
VA	0.824	0.481	9.739	−7.804	11.216
WA	−0.405	−1.041	9.766	−10.824	10.848
WI	1.457	0.953	7.903	−6.507	9.514

C. Aggregating Income Data

One potential limitation of our analysis is that we use aggregate national- and state-level data to compute IHD. To be more consistent with our model, we would have liked to use disaggregated income data from household surveys.

Unfortunately, no U.S. household-level data set has a time dimension long enough to allow estimation of an income hedging series that we could use in asset pricing tests. The use of aggregate income data is thus a necessary compromise.

Moreover, using aggregate income to compute IHD is consistent with the consumption and portfolio life-cycle literature. A common assumption in this literature is that household income growth is correlated with aggregate shocks and *not* idiosyncratic shocks. For example, Cocco, Gomes, and Maenhout (2005) "allow for correlation between innovations to excess stock returns and [household] labor income shocks through the aggregate component" of income growth (p. 495). Michaelides and Gomes (2005) make a similar assumption. Overall, using aggregate income is a reasonable approach in capturing the systematic component of individual households' income hedging.

D. Estimates of IHD

In this section, we examine whether the IHD measure exhibits significant variation over time. For the estimation, we assume that the only assets available to investors are four portfolios, namely, the market (RMRF), value-minus-growth (HML), small-minus-big (SMB), and winners-minus-losers (UMD) portfolios.[10] These portfolios are likely to capture the investment opportunity set of common investors reasonably well, and they are also the portfolios used for constructing common asset pricing factors.

D.1. Estimation Method

In our estimation, we replicate the inference methodology of the Bayesian worker in the model (see equation (2)). Specifically, we first estimate the vector of conditional covariances $\widehat{\boldsymbol{\Sigma}}_{y,r,t}$ between the returns of the four portfolios (RMRF, HML, SMB, UMD) and income in first-differences. To calculate the aggregate-level IHD, we use the covariances between the four portfolios and aggregate income in first-differences, while for the state-level IHD, we use the covariances between the four portfolios and state-level income in first-differences. Next, we estimate the conditional variance-covariance matrix for the returns of the four portfolios ($\widehat{\boldsymbol{\Sigma}}_{r,t}$). Finally, we multiply the negative value of the vector of income covariances by the inverse of the covariance matrix of returns ($-\widehat{\boldsymbol{\Sigma}}_{r,t}^{-1}\widehat{\boldsymbol{\Sigma}}_{y,r,t}$). The output of this multiplication is a vector of scaled covariances. We focus on the element corresponding to the HML factor, which is the IHD estimate for the HML factor.

To capture time-variation in the IHD estimates, we use a rolling estimation approach. Specifically, we set the rolling estimation window to 10 years (40 quarters) and compute new covariance estimates each quarter. This procedure yields a time series for IHD covering the period from Q1 1970 to Q4 2011. In

[10] In Table IA.III, we construct the IHD measure using different assumptions regarding the sets of financial assets that are available to investors.

Table II, we present summary statistics for IHD. We use the 10-year window to be consistent with the recent macro-finance literature. For example, Marfè (2017) uses 10-year rolling windows and quarterly data to calculate a time series of variance ratios in asset pricing tests.[11]

D.2. Time-Variation in IHD Estimates

The estimates of the HML hedging demand in Table II indicate that state-level IHDs vary over time. For example, the IHD of California's income with aggregate HML returns ranges from −3.100 (10^{th} percentile) to 6.623 (90^{th} percentile). Further, the standard deviation of the state-level IHD estimates is sizeable across states, varying from 2.248 (TN) to 18.218 (ND). The substantial time-variation in the state-level hedging measures is also clearly seen in Figure 1, Panel A. In the figure, we plot for each quarter the 10^{th} and 90^{th} percentile of the cross-sectional distribution of IHD. In almost all periods, some states exhibit positive and some exhibit negative IHD. Each quarter, we also compute the equal-weighted average IHD across states (State Avg), and report summary statistics for this measure at the bottom of Table II. The average IHD across states exhibits substantial time-series variation with a standard deviation of 4.654, and ranges from −3.262 (10^{th} percentile) to 8.849 (90^{th} percentile).

Last, we compute the IHD between HML returns and aggregate U.S. income in first-differences (Aggregate U.S. Income). We report summary statistics for this measure in Table III. Similar to the state-level results, we find strong time-series variation in the aggregate IHD. The strong time-variation in the national hedging term is also evident in Figure 1, Panel B.[12] In the figure, we plot the time series of the national IHD and the 95% confidence intervals of the average IHD. As shown in the figure, in many periods the national hedging term is outside these confidence interval bands.[13]

[11] We also consider alternative rolling window lengths for estimating IHD ranging from 8 to 15 years. We present these results in Table IA.II of the Internet Appendix. We find that lengthening the estimation window to 11, 12, or 13 years yields a statistically significant relation between IHD and HML returns. However, the main results fail to hold when extending the window to 14 or 15 years or shortening the window to 8 or 9 years. Among the alternative windows under consideration, the baseline 10-year window does not yield the strongest results statistically. Instead, the 12-year window yields the economically and statistically strongest IHD predictor (coefficient = −0.328, *t*-statistic = −2.77), which should alleviate concerns that our baseline window choice is the result of cherry-picking.

[12] Additionally, we present the time series of conditional correlations computed in the same way as the IHD measure in Figure IA.1 of the Internet Appendix.

[13] To further understand the time-series properties of the national IHD, we regress it on various combinations of lagged IHD, the set of factor premium predictors and macroeconomic measures from our baseline HML specifications, and an NBER recession indicator. We report the regression results in Table IA.IV of the Internet Appendix. We find that the IHD measure is highly persistent, with a very strong AR(1) coefficient across all specifications. Controlling for lagged IHD, few other explanatory variables are significantly related to IHD. In particular, of the factor premium predictors and baseline macroeconomic measures, IHD exhibits a strong positive relation only with unexpected GDP growth (*t*-statistic = 1.98).

Table II

Summary Statistics: State-Level IHD Estimates

This table reports the state-level IHD estimates of quarterly state income growth and national HML returns over the sample period. The state-level IHD is based on conditional covariances between quarterly state income growth and national HML returns over the past 40 quarters for each quarter during the sample period with 40 trailing observations. We also report the equal-weighted average for all statistics across states (State Avg). The sample period is from Q1 1970 to Q4 2011.

	IHD Estimates				
State	Mean	Median	Std. Dev.	10th pctile	90th pctile
AK	−0.162	−0.543	5.379	−6.144	7.544
AL	−1.749	−1.354	2.486	−1.491	5.156
AR	0.224	−0.521	4.148	−5.489	4.437
AZ	−0.826	−0.524	3.019	−2.685	4.164
CA	−1.025	−0.219	3.750	−3.100	6.623
CO	−2.045	−2.121	4.506	−3.274	8.757
CT	−0.666	−0.941	3.901	−2.851	4.513
DC	−5.455	−3.133	14.536	−13.570	30.19
DE	−3.892	−2.296	5.180	−1.159	12.103
FL	−0.930	−0.321	2.535	−2.494	4.689
GA	−1.609	−0.820	3.380	−1.950	5.637
HI	0.326	0.832	4.187	−5.972	4.735
IA	−5.638	−3.015	7.136	−1.972	14.111
ID	−0.979	−0.710	5.102	−5.066	9.204
IL	−1.365	−0.260	3.948	−3.194	6.205
IN	−2.314	−2.332	2.780	−1.114	5.735
KS	−4.005	−3.915	3.254	1.022	8.066
KY	−0.878	−0.751	3.222	−2.997	5.119
LA	−2.309	−1.739	3.439	−1.863	7.454
MA	−1.412	−1.220	4.068	−4.142	6.89
MD	−1.208	−1.468	3.886	−4.407	6.50
ME	0.476	0.541	2.996	−4.274	4.139
MI	−3.746	−3.152	4.312	−0.859	9.899
MN	−2.801	−1.932	5.715	−3.281	11.037
MO	−2.114	−2.633	3.605	−3.495	6.733
MS	−0.458	−0.188	3.168	−3.665	5.032
MT	−7.714	−0.871	13.553	−2.229	31.110
NC	−1.330	−0.980	2.659	−0.523	5.038
ND	−8.017	−4.894	18.218	−6.586	41.711
NE	−6.668	−6.481	4.958	0.535	12.285
NH	−0.754	0.482	4.520	−4.075	8.418
NJ	−1.679	−1.766	3.864	−3.490	7.182
NM	0.322	1.261	3.485	−3.826	5.640
NV	−3.578	−2.575	4.531	−1.349	11.007
NY	−1.056	−2.177	7.747	−10.919	11.345
OH	−2.930	−2.780	2.650	−0.036	6.382
OK	−1.593	0.356	4.521	−2.291	7.560
OR	−0.790	−0.731	2.402	−2.018	4.472
PA	−1.381	−0.289	3.040	−1.912	6.035
RI	0.669	0.078	2.525	−3.837	2.049
SC	−1.581	−2.062	2.592	−1.658	4.423

(Continued)

Table II—*Continued*

	IHD Estimates				
State	Mean	Median	Std. Dev.	10th pctile	90th pctile
SD	−5.004	−4.654	10.542	−7.539	21.358
TN	0.223	0.466	2.248	−2.541	3.247
TX	−1.287	−1.111	3.708	−3.715	6.999
UT	−0.608	−0.141	2.447	−2.336	4.453
VA	1.049	1.116	3.676	−5.065	4.021
VT	−1.788	−1.403	2.482	−0.466	5.814
WA	−5.611	−5.484	3.495	1.243	10.279
WI	−0.658	−0.057	3.048	−2.477	5.201
WV	−0.574	−1.373	5.025	−6.825	7.523
WY	−2.288	−0.594	5.790	−2.957	13.054
State Avg	−1.984	−1.400	4.654	−3.262	8.849
U.S. Income	−1.123	−0.115	3.269	−2.334	6.014

Taken together, our IHD estimates indicate that HML returns exhibit strong time-variation in their comovement with income at both the state and the aggregate level. The time-varying IHD estimates and the time-varying popularity of value/growth style portfolios (e.g., Kumar (2009)) suggest that switching between value and growth style portfolios might reflect the time-varying IHD for these styles.

III. Validating Hedging Demand Estimates

In this section, we present results from two validation tests, which are designed to investigate whether the IHD estimates for the HML factor capture actual time-variation in demands for value and growth stocks. First, we examine whether our covariance-based demand estimates are correlated with the portfolio weights of actual retail investors. Second, we investigate whether our IHD estimates are related to aggregate mutual fund flows.

A. Validation Using the Brokerage Data

In the first validation test, we use data on quarterly portfolio positions of retail investors at a major U.S. discount brokerage over the 1991 to 1996 period.[14] To align these holdings with our panel of state-level HML demand estimates, we calculate the relative weight in value and growth stock portfolios at the end of each quarter by investors located in each U.S. state. In particular, at the end of each quarter, we aggregate the holdings of all investors located in a given state in value and growth stocks. We define value (growth) stocks as those stocks with book-to-market in the highest (lowest) within-state quartile. Next, we denote the total holdings in value (growth) stocks of state s investors

[14] See Barber and Odean (2001) for details about the brokerage data.

Table III

Summary Statistics: Income Hedging Demand (IHD) Estimates for the HML Factor and Factor Predictors

This panel reports summary statistics for the aggregate IHD measure, which is based on the conditional covariances between quarterly U.S. income growth and the returns on the national HML portfolio (equation (3)) over the sample period. We also report summary statistics for factor predictors, which include the dividend yield on the value-weighted CRSP market index over the previous 12 months (DIV), the yield on the three-month T-bill (YLD), the difference between the average yields of Treasury bonds maturing in more than 10 years and those maturing in three months (TERM), and the difference between the average yields of bonds with a Moody's rating of AAA and bonds with a Moody's rating of BAA (DEF). We also report summary statistics for various macroeconomic controls, including industrial production growth, quarterly inflation, the Conference Board's Leading Economic Indicator (LEI) Index, and unexpected quarterly U.S. GDP growth (residuals from an AR(1) model). Further, we report summary statistics for value factor predictors, including the HML RISK-RETURN measure, the book-to-market (BM) spread (log book-to-market ratio of value stocks minus log book-to-market ratio of growth stocks), small book-to-market spread (book-to-market spread calculated among stocks with market capitalization falling in the lowest tercile of NYSE market capitalization in a given quarter), the difference in dividend yield on value stocks and the dividend yield on growth stocks over the previous 12 months, and lagged one-month HML return. Finally, we report summary statistics for various state-level control variables, including the average and maximum market capitalization of firms headquartered in a given state, and the growth in Office of Federal Housing Oversight (OFHEO) state house price indices. The sample period is from Q1 1970 to Q4 2011.

Variable	Mean	Median	Std. Dev.	10th pctile	90th pctile
IHD Estimates for the HML Factor					
Baseline, National Income Risk	−1.123	−0.115	3.269	−2.334	6.014
Baseline, State Income Risk	−1.661	−0.462	2.908	−1.303	5.816
Value-Growth	−4.101	−4.984	9.551	−8.967	13.168
Factor Predictors					
Dividend Yield (DIV)	2.515	2.391	0.980	1.254	3.988
Yield on 3-month T-bill (YLD)	5.387	5.140	3.192	0.940	9.060
Term Spread (TERM)	1.681	1.825	1.322	−0.150	3.310
Default Spread (DEF)	1.117	0.990	0.467	0.670	1.740
Macroeconomic Controls					
Industrial Production Growth	0.554	0.736	1.709	−1.461	2.481
Inflation Rate	1.079	0.889	0.880	0.311	2.429
Conf Board LEI Index	83.846	80.250	21.279	57.300	112.900
Unexpected Quarterly GDP Growth	−0.260	−0.262	3.329	−4.244	3.423
Value Factor Predictors					
RISK-RETURN	9.846	8.786	4.680	4.893	16.838
Value Spread	1.123	1.094	0.169	0.939	1.341
Small Stock Value Spread	1.178	1.144	0.158	1.013	1.430
Value Div Yield − Growth Div Yield	2.078	2.200	1.367	0.061	3.810
Lagged 1m HML Return	0.298	0.450	2.641	−2.960	3.720
State-Level Controls					
Average Market Cap ($ Millions)	1.094	0.521	1.260	150.176	2915.181
Maximum Market Cap ($ Millions)	42.929	14.623	72.453	2.043	125.429
State Housing Growth	1.108	1.055	2.124	−1.032	3.367

as $V_s(G_s)$ and calculate the relative weight in value versus growth stocks as follows: $VG_s = \frac{V_s - G_s}{V_s + G_s}$. To eliminate the effect of passive changes in portfolio weights due to price changes, we set the price of each stock equal to its average price during the 1991 to 1996 sample period.

To compare these direct measures of relative value-minus-growth holdings with our theoretical demand estimates, we regress the actual state-level value-minus-growth portfolio weights on the state-level IHD of the HML factor. In the regressions, we include additional controls (e.g., dividend yield, term spread, industrial production growth, inflation rate) to account for factors besides income hedging that could generate the observed variation in state-level HML holdings.

Apart from the IHD measure, we include another theory-motivated control variable. In particular, following equation (5), we compute a risk-return term based on the return of the HML portfolio scaled by the inverse of the variance-covariance matrix of returns. This scaled return is the element of the vector $\widehat{\boldsymbol{\Sigma}}_{r,t}^{-1}\widehat{\boldsymbol{\mu}}_{r,t}$ that corresponds to the HML. We denote the scaled return by the RISK-RETURN term and compute it using the same rolling-window estimation approach as the IHD measure.

We present the results from within-state panel regressions in Panel A of Table IV. In all specifications, we find that the observed value-minus-growth portfolio weights covary positively with our IHD measure. These positive estimates are consistent with the theoretical predictions of our model. In particular, as the income hedging potential of the HML factor increases, so does the IHD. Therefore, investors demand more of the value-minus-growth asset, increasing their weight in the overall portfolio. This evidence suggests that our hedging demand estimates capture the actual behavior of retail investors at the state level reasonably well.

B. Validation Using Aggregate Mutual Fund Flows

In our second validation test, we examine whether our IHD estimates are related to aggregate mutual fund flows. Since many investors allocate a significant proportion of their financial wealth into mutual funds (e.g., Polkovnichenko (2005)), it is possible that our measure of income hedging captures at least part of the time-variation in investors' relative preferences for mutual fund styles. To investigate this possibility, we examine whether net flows into value and growth mutual funds are correlated with our IHD measure.

We use data on quarterly mutual fund returns and total net assets from the CRSP mutual fund database to calculate fund-level flows. Following Cooper, Gulen, and Rau (2005), value funds are those with the style identifier *value/val* in the NAME field and growth funds are those with the style identifier *growth/gr/grth*. Following Frazzini and Lamont (2008), we calculate net flows for each fund as the difference between end-of-quarter total net assets (TNA) and the fund's calculated counterfactual end-of-quarter TNA. Counterfactual

Table IV

Validation Test Estimates

Panel A reports coefficient estimates from within-state panel regressions of the relative value-growth portfolio weight on state-level IHD and a set of factor predictors, macroeconomic controls, and value factor predictors described in Table III. We calculate the relative value-growth portfolio weight as the difference between end-of-quarter value and growth holdings divided by the sum of end-of-quarter value and growth holdings across all individuals in a given U.S. state using investor data from a large U.S. discount brokerage. The estimation period is from Q1 1991 to Q4 1996. t-statistics computed using standard errors adjusted for clustering at the state level are reported in parentheses below coefficient estimates. Panel B reports coefficient estimates from within-fund panel regressions of mutual fund flows on national-level IHD estimates, one-quarter-lagged fund return, and a set of factor predictors, macroeconomic controls, and value factor predictors described in Table III. We calculate the mutual fund flows as in Frazzini and Lamont (2008) and classify value and growth funds as in Cooper, Gulen, and Rau (2005). The estimation period is from Q1 1985 to Q4 2011. t-statistics computed using standard errors adjusted for clustering at the fund level are reported in parentheses below coefficient estimates.

	Panel A: State-Level Value-Growth Portfolio Weight				
Regressor	(1)	(2)	(3)	(4)	(5)
IHD	0.023	0.026	0.025	0.027	0.028
	(2.34)	(2.46)	(2.42)	(2.66)	(2.55)
RISK-RETURN	0.044	0.061	0.057	0.043	0.054
	(2.58)	(2.26)	(2.16)	(2.24)	(2.01)
DIV		−1.872			−1.581
		(−1.14)			(−0.75)
YLD		−0.001			−0.007
		(−0.04)			(−0.19)
TERM		0.020			−0.006
		(0.69)			(−0.26)
DEF		−0.029			−0.105
		(−0.15)			(−0.86)
Ind Prod Growth			0.018		−0.008
			(0.90)		(−0.56)
Inflation Rate			0.089		−0.002
			(1.18)		(−0.05)
LEI Index			0.003		0.022
			(0.63)		(1.79)
Unexp GDP Growth			−0.001		−0.001
			(−0.09)		(−0.07)

(Continued)

Table IV—*Continued*

Regressor	Panel A: State-Level Value-Growth Portfolio Weight				
	(1)	(2)	(3)	(4)	(5)
Value Spread				0.630	−1.730
				(0.61)	(−1.38)
Small Value Spread				0.082	2.902
				(0.16)	(3.02)
Value DivYld − Growth DivYld				−0.088	−0.062
				(−1.92)	(−1.56)
Lagged 1m HML Return				0.008	0.011
				(2.76)	(3.51)
Adj. R^2	0.076	0.092	0.081	0.099	0.108
Observations	717	717	717	717	717

	Panel B: Fund-Level Mutual Fund Flows					
	All Funds		Smaller Funds		Larger Funds	
Regressor	Value Funds (1)	Growth Funds (2)	Value Funds (3)	Growth Funds (4)	Value Funds (5)	Growth Funds (6)
IHD	0.007	−0.005	0.005	−0.007	0.004	−0.003
	(3.65)	(−3.52)	(1.38)	(−2.88)	(2.79)	(−2.73)
RISK-RETURN	0.031	0.002	0.046	0.004	0.023	0.004
	(11.05)	(1.24)	(8.29)	(1.14)	(9.40)	(3.07)
One-qtr lagged fund return	0.133	0.364	−0.188	0.213	0.292	0.350
	(1.44)	(6.70)	(−1.21)	(2.15)	(3.67)	(7.81)
DIV	−1.177	−1.781	−1.051	−1.586	−0.792	−0.991
	(−3.23)	(−6.91)	(−1.64)	(−3.66)	(−2.54)	(−5.03)
YLD	0.029	0.032	0.087	0.077	0.006	0.010
	(4.10)	(6.08)	(6.09)	(8.55)	(1.09)	(2.53)
TERM	0.045	0.032	0.111	0.078	0.015	0.007
	(5.88)	(6.06)	(7.23)	(7.92)	(2.46)	(1.71)

(Continued)

Table IV—*Continued*

	Panel B: Fund-Level Mutual Fund Flows					
	All Funds		Smaller Funds		Larger Funds	
Regressor	Value Funds (1)	Growth Funds (2)	Value Funds (3)	Growth Funds (4)	Value Funds (5)	Growth Funds (6)
DEF	−0.143	−0.091	−0.197	−0.115	−0.060	−0.035
	(−6.23)	(−6.02)	(−4.94)	(−4.74)	(−3.06)	(−2.97)
Ind Prod Growth	−0.001	0.009	−0.003	0.004	−0.001	0.009
	(−0.28)	(4.08)	(−0.57)	(0.89)	(−0.20)	(5.19)
Inflation Rate	−0.009	0.013	−0.022	0.007	0.001	0.015
	(−1.29)	(2.94)	(−1.87)	(0.84)	(0.24)	(4.04)
LEI Index	−0.011	−0.011	−0.020	−0.018	−0.006	−0.006
	(−13.80)	(−19.32)	(−11.94)	(−16.42)	(−9.23)	(−12.71)
Unexp GDP Growth	0.001	0.003	−0.002	0.003	0.002	0.002
	(0.46)	(3.10)	(−0.95)	(1.75)	(1.50)	(2.86)
Value Spread	0.504	0.211	0.520	0.278	0.292	0.227
	(3.58)	(2.03)	(2.09)	(1.69)	(2.38)	(2.77)
Small Value Spread	−0.859	−0.621	−1.178	−0.903	−0.498	−0.386
	(−6.55)	(−6.35)	(−5.09)	(−5.88)	(−4.30)	(−4.97)
Value DivYld − Growth DivYld	0.045	0.108	0.077	0.170	0.023	0.051
	(5.17)	(18.60)	(4.87)	(15.60)	(3.20)	(10.65)
Lagged 1m HML Return	0.005	−0.001	0.005	−0.004	0.004	−0.000
	(5.06)	(−1.63)	(2.93)	(−2.77)	(4.87)	(−0.89)
Adj. R^2	0.044	0.037	0.045	0.041	0.040	0.028
Observations	70,624	128,069	34,080	63,273	36,544	64,796
Value−Growth	0.012		0.012		0.007	
IHD loadings	(25.08)		(7.48)		(14.80)	

end-of-quarter TNA is the observed beginning-of-quarter TNA multiplied by the fund's observed return over the quarter plus a pro rata share (based on beginning-of-quarter TNA) of the total dollar flow to the mutual fund sector during the quarter.

To compare the actual net flows into value and growth mutual funds with our theoretical demand estimates, we regress fund-level net flows on the IHD of the HML factor. Panel B of Table IV presents estimates of such within-fund panel regressions, in which we also include a set of control variables. This set includes the RISK-RETURN term, the lagged fund returns to account for the performance-flow relation (e.g., Chevalier and Ellison (1997)), and macroeconomic variables such as industrial production growth and the inflation rate. See Section IV.A for a detailed description of all the control variables.

The regression estimates in column (1) show that average net flows into value funds covary positively with our IHD measure (estimate $= 0.007$, t-statistic $= 3.65$). In contrast, the regression estimates in column (2) show that average net flows into growth funds covary negatively with our IHD measure (estimate $= -0.005$, t-statistic $= -3.52$). Further, we find consistent results from specifications that focus on subsamples of smaller and larger funds (see columns (3) to (6)).

Taken together, these findings suggest that time-variation in the IHD estimate for HML reflects hedging-induced variation in investor demand for value and growth stocks. We conclude that income hedging appears to be an important determinant of style shifts among mutual fund investors.

IV. Income Hedging and Return Predictability

In this section, we test our key model prediction summarized in equation (5), which posits that an increase in the IHD of HML would lead to lower future HML returns. We test this key conjecture using a series of predictability regression models.

A. Return Predictability Regression Specifications

In our empirical analysis, we estimate the following regression specification:

$$r_{t+1}^{HML} = b_1 IHD_t^{HML} + \boldsymbol{b}'\boldsymbol{X}_t + u_{t+1},$$

where r_{t+1}^{HML} is the one-period-ahead HML return, IHD_t^{HML} is the element of the vector $-\widehat{\boldsymbol{\Sigma}}_{r,t}^{-1}\widehat{\boldsymbol{\Sigma}}_{y,r,t}$ that corresponds to the HML, and $\boldsymbol{X}$ is a vector of control variables.

In our empirical regressions, we are mainly interested in the sign and statistical significance of the coefficient estimate b_1. According to our model (see equation (5)), b_1 should be negative, so that a decrease in IHD, which corresponds to a decrease in the income hedging potential of HML, lowers current prices and increases future returns.

We calculate IHD estimates for the HML factor based on information at the end of the previous quarter. We use this end-of-quarter demand to predict the return of the HML portfolio over the subsequent quarter and over each month of the subsequent quarter. Specifically, we estimate the IHD of HML with 10 years of quarterly income data as of the end of quarter q and predict the return of the HML portfolio during quarter $q+1$ and during each of the three months of quarter $q+1$. For example, on December 31, we estimate demands using data until December 31 and then predict the HML return over the quarter ending March 31 as well as the one-month HML returns for the months of January, February, and March.

We use this estimation approach with mixed timing because the income data are available only at the quarterly frequency and the theoretical demand estimates can be calculated only quarterly. Therefore, we consider one-quarter-ahead predictability regressions. However, we also examine the strength of return predictability within the quarter with one-, two-, and three-month-ahead forecasting regressions.

In all of the predictability regressions, we account for a set of factor predictors, macroeconomic controls, and HML predictors. Conditional on these control variables, an increase in the IHD measure should not reflect improving investment opportunities in the overall market. Instead, this increase is likely to be driven by shifts in the income hedging potential of the HML portfolio.

The choice of control variables is motivated by existing literature. The set of controls includes the dividend yield (DIV) of the market index (CRSP VW index) over the previous 12 months, which has been shown to be associated with slow mean reversion in stock returns over the previous 12 months (Keim and Stambaugh (1986), Campbell and Shiller (1988), Fama and French (1988)). We control for the yield on the three-month T-bill (YLD), which is negatively related to future stock market returns and proxies for expectations of future economic activity (Fama (1981), Fama and Schwert (1977a)).

We also control for the term spread (TERM), which is the difference between the average yield on Treasury bonds with 20 years to maturity and the average yield of T-bills maturing in three months. The term spread is closely related to short-term business cycles (Fama and French (1988)). We account for the default spread (DEF), which is the difference between the average yield of bonds rated BAA by Moody's and the average yield of AAA-rated bonds. The default spread tracks long-term business cycle conditions (Fama and French (1988)). Further, the set of control variables includes important macroeconomic predictors such as industrial production growth, the inflation rate, the Leading Economic Indicator (LEI) index, and the unexpected component of GDP growth based on an AR(1) process.

Last, we account for important HML predictors. Specifically, we control for the value spread and the small-stock value spread (Cohen, Polk, and Vuolteenaho (2003)), the spread between the dividend yield of value firms and the dividend yield of growth firms over the past 12 months, as well as the previous month's HML return (Wahal and Yavuz (2013)). We also include in the regressions the RISK-RETURN term to capture variation in the investment opportunity set of the HML portfolio.[15]

B. One-Quarter-Ahead Return Predictability Regressions

We present our baseline predictability results in Table V, Panel A. We present estimates from one-quarter-ahead regressions and from one-, two-, and three-month-ahead regressions. In all specifications in Panel A, we calculate hedging demand estimates using national income (in first-differences). Our sample period is from Q1 1970 to Q4 2011.

We begin our analysis with one-quarter-ahead predictive regressions. In regression (1) of Panel A, we estimate a predictability regression using only the control variables. We find that the adjusted R^2 for this regression is 0.086. Most of the control variables are either statistically insignificant or marginally significant, with *t*-statistics ranging from −1.08 to 1.99. As expected, the two strongest predictors of the HML factor are the value spread and the difference in dividend yields between value and growth stocks (estimates = 19.293 and 1.343, *t*-statistics = 1.99 and 1.82, respectively).

In specification (2) of Panel A, the independent variable is the IHD associated with the HML factor. We find that this variable has a negative and statistically significant coefficient estimate (estimate = −0.295, *t*-statistic = −2.54). This estimate implies that a one-standard-deviation decrease in IHD for the HML factor is associated with a $0.295 \times 3.269 = 0.96\%$ increase in the HML return next quarter. Relative to the average quarterly HML returns over the sample period (=1.247%), this magnitude is economically meaningful. Further, the adjusted R^2 for this regression increases to 0.094. Overall, the estimates in specification (2) suggest that hedging-induced demand has an economically meaningful effect on future HML returns.

C. Monthly Return Predictability Estimates

Next, we examine within-quarter predictability and estimate one-, two-, and three-month ahead regressions. We present the monthly forecasting results in columns (3) to (8) of Panel A. For each month, we estimate regressions with and without the IHD estimates. The results suggest that our IHD measure has the strongest effect on returns during the one-month-ahead period. In specification (4), the estimate on the HML demand is −0.181 and the *t*-statistic is −2.35. We also find that the predictive power of the IHD weakens during the next two months.

We also formally examine long-term predictability following the same methodology as the long-term predictability literature (e.g., Lettau and Ludvigson (2001a)). This literature suggests that to assess long-term effects, one

[15] According to equation (5), the RISK-RETURN term is the element of $\widehat{\boldsymbol{\Sigma}}_t^{-1}\widehat{\boldsymbol{\mu}}_t$ that corresponds to the HML. We compute this term using the same 10-year rolling-window estimation approach as the IHD measure.

Table V

Predictive Regression Estimates for the Value Factor

Panel A reports coefficient estimates from regressions of one-quarter-ahead and h-month-ahead HML returns on the national-level IHD measure and a set of factor predictors. We calculate the IHD measure according to equation (3) using income changes at the national level and returns on the four portfolios (RMRF, SMB, HML, UMD). The factor predictors are as described in Table III. The estimation period is from Q1 1970 to Q4 2011. Panel B reports coefficient estimates from regressions of one-month-ahead HML returns on the national-level IHD measure and a set of factor predictors. We calculate the IHD measure for the HML factor using income changes at the national level and the returns of the four portfolios (RMRF, SMB, HML, UMD). The factor predictors are as described in Table III. In specification (3) (State-Level), we calculate the IHD measure using income at the state level and returns on the four portfolios (RMRF, SMB, HML, UMD), and then average these measures in each quarter, weighting each state by the fraction of national financial wealth held by state residents (calculated using IRS data on capital gains and dividend income). In specification (4) (Value-Growth), we separately calculate covariances for value and growth portfolios, and then take the difference. In specification (5) (Income Growth), we calculate the IHD measure between the value factor and U.S. income growth, instead of income changes. In specification (6), we report bias-adjusted estimates using the method of Amihud, Hurvich, and Wang (2009). The estimation period is from Q1 1970 to Q4 2011. t-statistics computed using Newey and West (1987) adjusted standard errors are reported in parentheses below coefficient estimates.

Panel A: Predictive Regressions

	Value Factor, 1-qtr ahead		Value Factor, h-month ahead					
Predictor, Month t	(1)	(2)	h=1 (3)	h=1 (4)	h=2 (5)	h=2 (6)	h=3 (7)	h=3 (8)
IHD		−0.295		−0.181		−0.073		−0.031
		(−2.54)		(−2.35)		(−1.30)		(−0.47)
RISK-RETURN		−0.018		0.018		0.033		−0.067
		(−0.19)		(0.31)		(0.62)		(−1.19)
DIV	0.404	−0.077	0.291	0.083	0.051	0.045	0.081	−0.163
	(0.28)	(−0.05)	(0.36)	(0.10)	(0.09)	(0.07)	(0.10)	(−0.20)
YLD	0.180	0.326	−0.108	−0.028	0.153	0.176	0.145	0.182
	(0.59)	(1.08)	(−0.68)	(−0.17)	(0.86)	(0.96)	(0.98)	(1.14)
TERM	0.499	0.620	0.376	0.434	0.111	0.120	0.009	0.057
	(0.97)	(1.21)	(1.26)	(1.43)	(0.46)	(0.48)	(0.04)	(0.25)
DEF	0.213	−0.188	0.054	−0.076	−0.290	−0.240	0.378	0.080
	(0.19)	(−0.17)	(0.07)	(−0.10)	(−0.49)	(−0.37)	(0.64)	(0.13)
Ind Prod Growth	0.311	0.292	0.234	0.243	0.111	0.133	−0.028	−0.075
	(0.91)	(0.79)	(0.87)	(0.86)	(0.52)	(0.57)	(−0.21)	(−0.54)

(Continued)

Table V—*Continued*

Panel A: Predictive Regressions

Predictor, Month t	Value Factor, 1-qtr ahead (1)	Value Factor, 1-qtr ahead (2)	Value Factor, h-month ahead h=1 (3)	h=1 (4)	h=2 (5)	h=2 (6)	h=3 (7)	h=3 (8)
Inflation Rate	0.698	0.366	0.928	0.782	−0.109	−0.117	−0.154	−0.317
	(0.76)	(0.40)	(1.90)	(1.66)	(−0.25)	(−0.25)	(−0.46)	(−0.88)
LEI Index	0.045	0.051	0.027	0.033	0.007	0.011	0.009	0.007
	(0.78)	(0.97)	(0.98)	(1.21)	(0.31)	(0.46)	(0.30)	(0.23)
Unexp GDP Growth	0.286	0.279	0.182	0.176	0.020	0.015	0.085	0.089
	(1.49)	(1.51)	(1.39)	(1.38)	(0.28)	(0.22)	(1.27)	(1.34)
Value Spread	19.293	20.071	7.922	9.079	9.951	11.012	1.248	−0.166
	(1.99)	(2.12)	(1.72)	(1.91)	(2.06)	(2.33)	(0.27)	(−0.04)
Small Value Spread	−7.484	−8.397	−3.619	−4.615	−4.943	−5.725	1.132	1.995
	(−1.08)	(−1.32)	(−1.03)	(−1.34)	(−1.64)	(−1.96)	(0.36)	(0.64)
Value DivYld − Growth DivYld	1.343	1.596	0.901	1.012	0.396	0.401	0.001	0.128
	(1.82)	(2.04)	(2.05)	(2.07)	(1.18)	(1.14)	(0.00)	(0.37)
1m HML Return	0.314	0.298	0.012	−0.001	0.336	0.328	−0.030	−0.025
	(1.35)	(1.29)	(0.09)	(−0.01)	(1.87)	(1.82)	(−0.22)	(−0.19)
Constant	−22.211	−21.545	−10.169	−10.663	−7.343	−8.333	−4.444	−2.386
	(−1.66)	(−1.63)	(−1.58)	(−1.55)	(−1.05)	(−1.18)	(−0.66)	(−0.36)
Adj. R^2	0.086	0.094	0.085	0.098	0.115	0.110	−0.038	−0.042
Quarters	168	168	168	168	168	168	168	168

Panel B: Predictive Regressions, 1-month-ahead Value Factor

Variations in IHD Measure		National	State-Level	National Value−Growth	National Income Growth	National Bias-Adjusted
Sample Period	1970–2011	1970–2011	1970–2011	1970–2011	1970–2011	1970–2011
Predictor, Month t	(1)	(2)	(3)	(4)	(5)	(6)
IHD		−0.181	−0.184	−0.067	−0.250	−0.170
		(−2.35)	(−2.11)	(−2.16)	(−2.30)	(−2.21)

(Continued)

Table V—*Continued*

	Panel B: Predictive Regressions, 1-month-ahead Value Factor					
Variations in IHD Measure		National	State-Level	National Value−Growth	National Income Growth	National Bias-Adjusted
Sample Period	1970–2011	1970–2011	1970–2011	1970–2011	1970–2011	1970–2011
Predictor, Month t	(1)	(2)	(3)	(4)	(5)	(6)
RISK-RETURN		0.018	0.026	0.040	0.024	0.028
		(0.31)	(0.44)	(0.66)	(0.40)	(0.49)
DIV	0.291	0.083	0.194	0.078	0.223	0.028
	(0.36)	(0.10)	(0.23)	(0.09)	(0.26)	(0.03)
YLD	−0.108	−0.028	−0.060	−0.018	−0.046	−0.029
	(−0.68)	(−0.17)	(−0.36)	(−0.11)	(−0.28)	(−0.17)
TERM	0.376	0.434	0.407	0.471	0.428	0.435
	(1.26)	(1.43)	(1.34)	(1.51)	(1.41)	(1.43)
DEF	0.054	−0.076	−0.088	0.183	−0.018	−0.121
	(0.07)	(−0.10)	(−0.11)	(0.25)	(−0.02)	(0.16)
Ind Prod Growth	0.234	0.243	0.260	0.248	0.253	0.246
	(0.87)	(0.86)	(0.91)	(0.88)	(0.90)	(0.87)
Inflation Rate	0.928	0.782	0.817	0.856	0.810	0.782
	(1.90)	(1.66)	(1.72)	(1.77)	(1.69)	(1.66)
LEI Index	0.027	0.033	0.035	0.038	0.039	0.036
	(0.98)	(1.21)	(1.27)	(1.36)	(1.41)	(1.34)
Unexp GDP Growth	0.182	0.176	0.174	0.184	0.175	0.176
Value Spread	7.922	9.079	8.723	9.863	8.986	8.836
	(1.72)	(1.91)	(1.83)	(2.14)	(1.90)	(1.86)
Small Value Spread	−3.619	−4.615	−3.876	−4.788	−4.505	−4.791
	(−1.03)	(−1.34)	(−1.13)	(−1.40)	(−1.30)	(−1.39)
Value DivYld −	0.901	1.012	0.993	0.855	1.017	1.007
Growth DivYld	(2.05)	(2.07)	(2.04)	(1.83)	(2.08)	(2.06)
1m HML Return	0.012	−0.001	−0.006	0.017	0.000	−0.001
	(0.09)	(−0.01)	(−0.05)	(0.14)	(0.00)	(−0.01)
Constant	−10.169	−10.663	−11.328	−12.050	−11.680	−10.663
	(−1.58)	(−1.55)	(−1.64)	(−1.81)	(−1.70)	(−1.55)
Adj. R^2	0.086	0.094	0.085	0.098	0.115	0.110
Quarters	168	168	168	168	168	168

should focus on cumulative returns. We therefore compute cumulative HML returns over holding periods ranging from 1 to 24 months. We plot the estimates of the various long-term regressions in Figure IA.2 of the Internet Appendix together with ± 2 standard error bands. The standard errors use a dynamic Newey and West (1987) adjustment. We find that the IHD measure is a statistically significant predictor of cumulative HML returns over holding periods of up to 15 months. This finding suggests that the IHD-induced predictability is strong in the medium term.

We use the one-quarter-ahead regression estimates to examine whether the observed HML returns align with the HML returns implied by our model. Specifically, Figure 1 suggests that the value premium should be lower or negative in the second half of the 1980s and in the period 1992 to 2001, that is, during the tech boom. To examine whether these observations align with our model, in Figure IA.3 of the Internet Appendix we plot the expected HML returns implied by our main specification against the realized HML returns over the sample period. The correlation between the two series is 0.417 and is highly statistically significant, with a p-value of less than 0.0001. Further, we find that both the implied and realized HML returns are relatively low in the late 1980s and from 1992 to 2001.

To summarize, the results in Panel A of Table V indicate that our IHD for the HML portfolio can forecast future HML returns. This predictability is the strongest one month ahead but it is persistent for more than one year. In light of these findings, in the rest of our analysis, we focus exclusively on one-month-ahead predictive regressions and provide additional evidence supporting the income hedging mechanism.

D. Robustness of Monthly Return Predictability Estimates

In Panel B of Table V, we focus exclusively on one-month-ahead predictability regressions and provide evidence from various robustness tests. To facilitate comparison, regression (1) in Panel B reports estimates from the predictability regression that uses only the set of control variables as predictors. Regression (2) presents the baseline results for the IHD measure based on national income.

In our first robustness check, we adopt a more disaggregated approach in computing the IHD. In this case, we first compute IHD at the state level. We then aggregate the state-level demands to the national level, weighting each state by the fraction of national financial wealth held by state residents.[16] We report the estimation results in column (3) of Panel B. The coefficient estimate on the new IHD is almost identical to the estimate in column (2), although its statistical significance is weaker (t-statistic $= -2.11$).

In our next tests, we show that the significance of the IHD estimated with national income data is robust to alternative estimation methodologies. Specifically, in column (4), we separately calculate the IHD of the value and growth

[16] The fraction of national financial wealth held by state residents is calculated using IRS data on capital gains and dividend income reported on tax returns at the state level.

portfolios with aggregate income and then take the difference. In column (5), we calculate the IHD using income growth instead of income in first-differences. In our baseline analysis, we use income in first-differences to be consistent with our model in Section I. The results in columns (4) and (5) indicate that the coefficient estimate on IHD remains negative and statistically significant.

Following Stambaugh (1999), we examine the potential biases in estimates of the HML demand coefficient. Stambaugh (1999) shows that the estimates in predictability regressions can be biased if the predictors are persistent and endogenous. As shown in Table IA.IV of the Internet Appendix, the IHD demand is persistent and thus it is possible that our original OLS estimates are biased. Our bias-adjustment estimation follows the multivariate method of Amihud, Hurvich, and Wang (2009). The results for the bias-corrected IHD are in column (6) of Table V, Panel B.

The corrected estimate in column (6) is -0.170 (t-statistic $= -2.21$). This value is very close to the baseline estimate in column (2) of Panel B (estimate $=$ 0.181, t-statistic $= 2.35$). The two estimates are similar because the estimation bias is small. Specifically, we find that, even though the persistence in IHD is high (see the high AR(1) coefficient in Table IA.IV of the Internet Appendix), the level of endogeneity (i.e., the correlation between the error terms from the predictability regression and the AR(1) model of the predictor) is low (correlation $= 0.05$).

We also examine the robustness of our results to excluding episodes in which IHD exhibits sharp increases and declines, as these are potentially influential observations. In particular, we focus on two episodes: the sharp increase and subsequent decline in the early 1990s and the sharp permanent increase in Q4 2003. To remove the effect of these two episodes, we respectively exclude observations in the Q4 1990 to Q4 1992 and Q2 2003 to Q2 2004 periods. We also consider the case in which we exclude both of these periods. We report these results in Table IA.V of the Internet Appendix. In all cases, we find that our results are robust to excluding potentially influential observations. Interestingly, we find that our results are stronger, both economically and statistically, when we exclude the short-lived spike in IHD in the early 1990s.

In our final robustness test, we decompose IHD into its components. Our goal is to show that the variation in IHD that forecasts returns is related to the numerator (i.e., the income-HML covariance) and not the denominator (i.e., the HML variance). Specifically, we decompose the IHD measure into three components: (i) the income-HML covariance, (ii) the HML variance, and (iii) a residual term equal to IHD minus the sum of the income-HML covariance and negative one times the HML variance. We find that the income-HML covariance predicts a higher next-month HML return, with a t-statistic of 1.72. In contrast, the denominator and residual components have insignificant coefficient estimates, with t-statistics of just 0.83 and -0.83, respectively.

Overall, our results suggest that time-variation in the value factor is driven in part by the time-varying effectiveness of the HML factor as a hedge against income risk. In particular, our findings imply that a rise in the income hedging potential of the HML factor at the end of the quarter creates price pressure for HML-component stocks, resulting in lower future returns in the short to medium term.

V. Income Hedging and State-Level Asset Prices

Our analysis so far focuses on predicting the aggregate HML factor return. In this section, we examine whether state-level HML returns can be predicted more effectively using local measures of hedging-induced demand. This analysis is motivated by the observation that income risk faced by individuals is likely to vary geographically. Further, high levels of local stock ownership may be explained in part by income hedging motives. Van Nieuwerburgh and Veldkamp (2009) show that if local investors have an initial information advantage on local stocks, they may specialize in these stocks and potentially hold a portfolio of local stocks that minimizes their income risk. Hence, local investors may optimally choose which local stocks to hold based on their hedging potential.

Our state-level analysis is also motivated by the local bias literature, which demonstrates that investors exhibit a preference for local stocks and these preferences could affect stock prices (e.g., Coval and Moskowitz (2001), Korniotis and Kumar (2013)). Specifically, Korniotis and Kumar (2013) find that within-state ownership of state-headquartered firms is high among both retail and institutional investors, and that time variation in state-level ownership affects the returns of local firms.

In light of these findings, we examine whether hedging-induced shifts in local asset demands affect the returns of local value and growth portfolios. Specifically, we posit that if investors in a state overweight stocks of firms located in that state, then the local HML portfolio will exhibit low future returns when the local IHD is high. We examine this conjecture using state-level IHD estimates and the returns of the state-level HML portfolios.

A. State-Level HML Returns

We construct state-level HML portfolios using monthly stock returns, stock prices, and shares outstanding from CRSP. We restrict the sample to common stocks (i.e., share codes of 10 or 11). We merge these observations with firm headquarters data from Compustat. We also compute book-to-market ratios for each firm using data from Compustat. The book-to-market ratio is the sum of year-end book equity and balance sheet deferred taxes divided by year-end market equity. We assume the standard six-month lag between measurement and observation periods.

We calculate quarterly state-level HML portfolio returns by sorting stocks headquartered within each state using their book-to-market ratio. We then calculate the state HML return as the return of a value-weighted portfolio of stocks that assumes a long (short) position in the stocks of firms with a book-to-market ratio in the highest (lowest) within-state quartile. To ensure that the state-level HML returns are economically meaningful, we limit attention to states with at least 30 firms headquartered in the state during a given quarter.

Our portfolio construction procedure yields state HML time series for 35 states. We present summary statistics for state-level HML returns in Table I. The summary statistics indicate that state-level value factors offer positive average returns for almost all states, except AR, IA, IL, and WA. Further, state value factor returns exhibit high volatility. The standard deviation of returns ranges from 4.821% (IL) to 12.136% (UT).

B. Local Hedging Demand and Local Predictability

We examine the predictability of state-level HML portfolios using panel predictive regressions. In columns (1) to (3) of Table VI, we report estimates from within-state panel regressions of one-month-ahead state-level HML returns on state-level IHD. As described in Section II.D.1, state-level IHD is constructed using the covariances between state-level income and the returns of the four aggregate portfolios (RMRF, HML, SMB, UMD).[17]

The panel regression specifications contain the aggregate control variables used previously (see Tables IV and V) as well as state-level predictors. The state-level predictors include average firm size, maximum firm size, and average housing growth. The specifications also include state-level fixed effects. The estimation period for the panel regressions is from Q1 1970 to Q4 2011. We consider only 35 states in our estimation. This set includes states for which we have at least 30 firms so that state-level value and growth portfolios are well defined.

The estimates in Table VI show that state-level IHDs predict one-month-ahead local HML returns. In the univariate panel regression (1), the coefficient estimate on the state-level IHD is -0.093 (t-statistic $= -3.44$). This estimate remains negative and statistically significant (estimate $= -0.105$, t-statistic $= -3.53$) even when we add all of the market-wide and state-level predictors (see columns (2) and (3)). Taken together, the state-level panel regressions provide evidence that growing local demand for the HML portfolio at the beginning of a month induces price pressure that generates a low return for the local HML portfolio during the following month.

C. Subsamples Based on Local Ownership

If local hedging demands generate predictable patterns in local HML returns, the evidence of predictability should be stronger or even exclusively concentrated among stocks with high local ownership. To test this conjecture, we examine the effects of local ownership on local HML return predictability.

We identify the percentage ownership of a firm that is local using retail investor data from a large U.S. discount brokerage house, which covers the

[17] For robustness, in Section IV of the Internet Appendix we construct the state-level IHD using state-level income and state-level HML portfolio returns. The predictability results for this alternative state-level IHD measure are very similar to those presented here.

Table VI

State-Level Panel Predictive Regression Estimates

This table reports estimates from within-state panel regressions of the one-month-ahead state-level HML return on state-level IHD measures. The state-level HML return is calculated as the return on a value-weighted portfolio of stocks headquartered in a given state that goes long (short) in the stocks of firms with a book-to-market ratio in the highest (lowest) within-state quartile. The state-level IHD measure is constructed based on equation (3) using state-level income and returns on the four aggregate portfolios (RMRF, SMB, HML, UMD). The local ownership conditional state-level value factor is calculated by first conditioning on high- or low-local-ownership stocks (above or below median in the cross-section of CRSP stocks in a given month), and then calculating the return from a value-weighted portfolio of stocks headquartered in a given state that goes long (short) in the stocks of firms with a book-to-market ratio in the highest (lowest) within-state quartile. All specifications include factor predictors described in Table III. The estimation period is from Q1 1970 to Q4 2011. t-statistics computed using standard errors adjusted for clustering at the state level are reported in parentheses below coefficient estimates.

				High-Local-Ownership Stocks			Low-Local-Ownership Stocks		
Predictor, Month t	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IHD	−0.093	−0.108	−0.105	−0.052	−0.100	−0.081	−0.072	−0.072	−0.096
	(−3.44)	(−3.78)	(−3.53)	(−1.83)	(−2.81)	(−2.07)	(−1.60)	(−1.37)	(−1.51)
RISK-RETURN	−0.068	−0.068	−0.071	−0.044	−0.071	−0.080	−0.059	−0.038	−0.038
	(−2.90)	(−2.45)	(−2.59)	(−1.74)	(−1.96)	(−2.22)	(−2.43)	(−0.90)	(−0.80)
DIV		0.425	1.172		−0.913	−0.554		0.794	1.006
		(0.92)	(2.37)		(−1.77)	(−0.91)		(1.13)	(1.22)
YLD		−0.453	−0.457		−0.237	−0.228		−0.409	−0.433
		(−4.92)	(−4.48)		(−1.93)	(−2.06)		(−2.54)	(−2.48)
TERM		−0.220	0.012		−0.269	−0.111		−0.149	−0.072
		(−1.36)	(0.06)		(−1.21)	(−0.46)		(−0.77)	(−0.30)
DEF		1.196	1.320		1.822	1.826		0.968	1.238
		(2.46)	(2.47)		(3.67)	(3.96)		(1.47)	(1.62)
Ind Prod Growth		−0.282	0.036		0.196	0.447		−0.161	0.096
		(−2.44)	(0.32)		(1.10)	(2.48)		(−0.93)	(0.52)
Inflation Rate		0.424	0.444		−0.234	−0.257		0.317	0.319
		(1.98)	(1.96)		(−0.54)	(−0.60)		(0.89)	(0.87)
LEI Index		0.025	0.070		−0.015	−0.005		0.024	0.056
		(1.76)	(3.47)		(−0.84)	(−0.20)		(1.41)	(1.89)

(Continued)

Table VI—*Continued*

				High-Local-Ownership Stocks			Low-Local-Ownership Stocks		
Predictor, Month t	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unexp GDP Growth		0.387	0.287		0.255	0.137		0.247	0.177
		(8.88)	(6.58)		(2.77)	(1.73)		(3.61)	(2.32)
Value Spread		8.612	8.156		3.123	0.879		10.461	10.480
		(3.69)	(3.52)		(1.19)	(0.40)		(2.29)	(2.08)
Small Value Spread		−0.462	1.346		3.116	5.716		−3.105	−2.497
		(−0.30)	(0.72)		(1.19)	(2.21)		(−0.88)	(−0.63)
Value DivYld −		1.516	1.546		1.166	1.170		1.103	1.066
Growth DivYld		(9.11)	(8.40)		(5.73)	(5.53)		(4.87)	(4.54)
1m HML Return		−0.004	−0.002		−0.049	−0.040		0.068	0.049
		(−0.13)	(−0.06)		(−1.11)	(−0.88)		(2.42)	(1.53)
State Avg. Firm Size			−0.566			−0.181			−0.669
			(−1.95)			(−0.64)			(−2.38)
State Max Firm Size			0.010			0.010			0.004
			(3.12)			(2.80)			(1.28)
State Housing Growth			0.067			0.161			0.025
			(1.64)			(2.19)			(0.29)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.004	0.050	0.047	0.001	0.037	0.040	0.003	0.036	0.033
U.S. States	35	35	35	27	27	27	19	19	19
State-Quarter Observations	4,485	4,485	4,130	2,651	2,651	2,570	1,900	1,900	1,765

period from 1991 to 1996.[18] For each month in the retail data set and for each firm, we measure the percentage of shares outstanding held by investors in the state where the firm is headquartered. Based on the average value of the monthly ownership measures for each firm, we sort firms into high or low local ownership categories.

For each U.S. state, we calculate the HML returns separately for high local ownership and low local ownership firms. For each local ownership category, we calculate state-level HML portfolio returns as before. Specifically, we sort all stocks headquartered in a given state and in a given local ownership category by book-to-market ratio. We then form a long(short) portfolio of stocks by value-weighting firms with a book-to-market ratio in the highest (lowest) within-state quartile. To have meaningful ownership-based state HML portfolios, we continue to impose the 30-firm minimum requirement for each local ownership subsample when sorting on book-to-market ratio at the state level.

We present the predictability regression estimates for both local ownership subsamples in columns (4) to (9) of Table VI. For each local ownership-based subsample, we regress one-month-ahead state-level HML returns on the state-level IHD measures. The estimation results reveal that our evidence of predictability of the local HML portfolios by the local IHD is concentrated among firms with high local ownership. In particular, the coefficient estimate for the high local ownership subsample in column (6), where we control for all predictors, is −0.081 and statistically significant (t-statistic = −2.07). In contrast, the coefficient estimate for the low local ownership subsample in column (9) is weak (estimate = −0.096, t-statistic = −1.51).

D. Long-Short Portfolio Performance Estimates

The evidence from the state-by-state predictability regressions illustrates that local HML portfolio returns are related to the variability in local IHDs. Next, we construct a long-short portfolio that exploits the cross-sectional variation in state-level HML demand estimates. The performance of this portfolio provides out-of-sample evidence of the economic significance of our predictability regressions.

We define portfolios by sorting the state-level HML portfolios using our estimates for the state-level IHD measure. We form six portfolios. The Long (Short) portfolio is an equal-weighted portfolio of the three states with the lowest (highest) HML IHD at the end of a month and thus predicted to have the highest (lowest) HML return in the next month. The Long–Short portfolio captures the difference in the returns of the Long and Short portfolios. The final three portfolios, that is, portfolios 2 to 4, are equal-weighted portfolios of the remaining states sorted into terciles based on their respective HML demands. Portfolios are formed at the beginning of each quarter and are held for one month. The

[18] The retail sample is well represented across all U.S. states. In particular, the distribution of households across states is very similar between the retail investor sample and the Census data. See Barber and Odean (2000) and Appendix D of Korniotis and Kumar (2011) for additional details.

Table VII

State-Level IHD Portfolios: Performance Estimates

This table reports performance estimates of a long-short portfolio defined using the IHD measure of the local value-growth factor. Component returns are those of value-weighted state-level value-growth portfolios. We report the performance of six portfolios: the Short portfolio, which is an equal-weighted portfolio of the three states predicted to have the lowest value-growth returns in the next month, the Long portfolio, which is an equal-weighted portfolio of the three states predicted to have the highest value-growth returns in the next month, the Long–Short portfolio, which captures the difference in the returns of the Long and Short portfolios, and portfolios 2, 3, and 4, which are equal-weighted portfolios of the remaining states sorted into terciles based on predicted value–growth returns in the next month. Portfolios are formed at the beginning of each quarter and are held for one month. Long–Short portfolio profits are then invested in the risk-free asset for the second and third months of each quarter. In Panel A, we report raw and characteristic-adjusted portfolio returns. Characteristic-adjusted returns are computed using the method of Daniel et al. (1997). *t*-statistics computed using Newey and West (1987) adjusted standard errors are reported in parentheses below the estimates. In Panel B, we report the standard deviation and Sharpe ratio for each portfolio. The portfolio formation period is from Q1 1970 to Q4 2011.

	Panel A: Portfolio Returns	
Portfolio	Raw Return	Char-Adj Return
1 (Short)	0.944	−0.107
	(2.18)	(−0.35)
2	0.641	0.222
	(1.53)	(0.82)
3	1.356	0.684
	(3.66)	(2.50)
4	1.257	0.465
	(3.85)	(2.46)
5 (Long)	2.312	1.419
	(5.02)	(3.48)
Long−Short	1.369	1.525
	(2.73)	(2.77)
Quarters	168	168

	Panel B: Portfolio Performance Characteristics (Excess raw returns)	
Portfolio	Std Dev	Sharpe Ratio
1 (Short)	6.851	−0.055
2	5.705	−0.119
3	5.465	0.006
4	5.243	−0.012
5 (Long)	6.417	0.154
Long−Short	6.378	0.215

Long–Short portfolio profits are then invested in the risk-free asset for the second and third months of each quarter.

Table VII reports quarterly performance estimates of the six portfolios. In Panel A, we report raw and characteristic-adjusted portfolio returns. The characteristic-adjusted returns are computed using the Daniel et al. (1997) method. The *t*-statistics, which are computed using Newey and West (1987) standard errors, are reported in parentheses below the estimates. In Panel B, we report the standard deviation and the Sharpe ratio for each portfolio. The sample period is from Q1 1970 to Q4 2011.

The performance estimates show that the Long portfolio significantly outperforms the Short portfolio. For example, the quarterly characteristic-adjusted return for the Long portfolio is 1.419% (t-statistic = 3.48), the Short portfolio has a characteristic-adjusted return of −0.107% (t-statistic = −0.35), and the Long–Short portfolio earns 1.525% per quarter (t-statistic = 2.77). We find similar results when we examine the portfolio Sharpe ratios. The Sharpe ratios of the Short, Long, and Long–Short portfolios are −0.055, 0.154, and 0.215, respectively.

We further examine the performance of our portfolios using various factor models. In particular, we estimate factor regressions for the Short, Long, and Long–Short portfolio returns. The factor models contain some combination of the following factors: the market excess return (RMRF), the size factor (SMB), the value factor (HML), the momentum factor (UMD), two reversal factors (short-term reversal (STR) and long-term reversal (LTR)), and the liquidity factor (LIQ). We report the quarterly alpha estimates and factor exposures in Table VIII. The t-statistics computed using Newey and West (1987) adjusted standard errors are reported in parentheses below the estimates.

Consistent with the performance estimates in Table VII, the alpha estimates of the Long–Short portfolio in Table VIII are positive and consistently significant. For example, the alpha estimate for the Long–Short portfolio from the model that includes all of the factors (RMRF, SMB, HML, UMD, STR, LTR, and LIQ; see column (12)) is 1.304% (t-statistic = 2.38). Overall, these performance estimates indicate that the predictive power of the HML demand estimates is strong out of sample, even when we consider various factor models to account for risk differences across portfolios.

VI. Additional Evidence and Robustness Tests

In this section, we present additional evidence on the relation between income hedging and return predictability that we document. We also relate our work to existing research and present various additional robustness tests.

A. Occupational Risk

We provide more evidence that our results are related to income hedging following Davis and Willen (2000). They show that across 10 occupation categories, electrical engineers face the highest income risk and auto mechanics the lowest. Similar to Davis and Willen (2000), we use data from the Current Population Survey (CPS) to construct annual income growth series for electrical engineers and auto mechanics and calculate occupation-specific IHD estimates. Since the CPS income growth series are only available from 1968

Table VIII

State-Level IHD Portfolios: Factor Model Estimates

This table reports factor model estimates of a long-short portfolio defined using the IHD measure of the local value-growth factor. Component returns are excess returns of value-weighted state-level value-growth portfolios. We consider estimates of i) the Long portfolio, which is an equal-weighted portfolio of the three states predicted to have the highest value-growth returns in the next month, ii) the Short portfolio, which is an equal-weighted portfolio of the three states predicted to have the lowest value-growth returns in the next month, and iii) the Long–Short (L–S) portfolio, which captures the difference in the returns of the Long and Short portfolios. Portfolios are formed at the beginning of each quarter and are held for one month. Long–Short portfolio profits are then invested in the risk-free asset for the second and third months of each quarter. The factor models contain some combination of the following factors: the market excess return (RMRF), the size factor (SMB), the value factor (HML), the momentum factor (UMD), two reversal factors (short-term reversal (STR) and long-term reversal (LTR)), and the liquidity factor (LIQ). t-statistics computed using Newey and West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from Q1 1970 to Q4 2011.

Factor	Long (1)	Short (2)	L–S (3)	Long (4)	Short (5)	L–S (6)	Long (7)	Short (8)	L–S (9)	Long (10)	Short (11)	L–S (12)
Alpha	1.030	−0.315	1.345	0.155	−1.133	1.288	0.529	−0.787	1.316	0.412	−0.892	1.304
	(2.09)	(−0.78)	(2.59)	(0.37)	(−2.70)	(2.63)	(1.12)	(−1.26)	(2.41)	(0.91)	(−1.43)	(2.38)
RMRF	−0.026	−0.041	0.015	−0.008	−0.029	0.021	−0.057	−0.040	−0.017	0.010	0.016	−0.006
	(−0.35)	(−0.51)	(0.20)	(−0.12)	(−0.37)	(0.22)	(−0.79)	(−0.48)	(−0.17)	(0.14)	(0.18)	(−0.06)
SMB				0.383	0.372	0.011	0.292	0.269	0.023	0.326	0.299	0.027
				(3.97)	(3.47)	(0.10)	(3.62)	(2.45)	(0.20)	(3.95)	(2.75)	(0.23)
HML				0.530	0.494	0.036	0.470	0.383	0.087	0.499	0.408	0.090
				(7.63)	(3.84)	(0.25)	(6.02)	(2.67)	(0.56)	(6.28)	(2.70)	(0.58)
UMD							−0.160	−0.118	−0.042	−0.163	−0.120	−0.043
							(−2.55)	(−0.92)	(−0.40)	(−2.98)	(−0.97)	(−0.41)
STR							0.101	−0.033	0.134	0.089	−0.043	0.132
							(0.73)	(−0.17)	(1.06)	(0.63)	(−0.22)	(1.03)
LTR							−0.002	0.180	−0.182	−0.041	0.145	−0.186
							(−0.03)	(1.73)	(−1.51)	(−0.55)	(1.40)	(−1.54)
LIQ										−0.111	−0.094	−0.017
										(−2.43)	(−1.76)	(−0.45)
Adj. R^2	−0.005	−0.003	−0.006	0.314	0.243	−0.017	0.353	0.258	−0.002	0.371	0.268	−0.009
Quarters	168	168	168	168	168	168	168	168	168	168	168	168

Table IX

Predictive Regression Estimates: Occupational Risk

This table reports coefficient estimates from regressions of the one-month-ahead HML return on occupation-specific IHD estimates and a set of factor predictors, macroeconomic controls, and value factor predictors described in Table III. In column (1), we compute IHD using the real annual income growth series of electrical engineers. In column (2), we compute IHD using the real annual income growth series of auto mechanics. Both annual income growth series are constructed using data from the Current Population Survey, following Davis and Willen (2000). The estimation period is from 1977 to 2011. t-statistics computed using Newey and West (1987) adjusted standard errors are reported in parentheses below coefficient estimates.

Predictor, Month t	Electrical Engineers (1)	Auto Mechanics (2)
IHD	−0.095	0.054
	(−1.92)	(0.78)
RISK-RETURN	−0.204	−0.142
	(−1.11)	(−0.76)
DIV	2.563	2.665
	(1.10)	(1.15)
YLD	−0.578	−0.049
	(−0.71)	(−0.07)
TERM	0.901	1.474
	(1.16)	(2.28)
DEF	0.019	1.004
	(0.02)	(0.61)
Ind Prod Growth	0.824	0.586
	(1.36)	(1.07)
Inflation Rate	2.334	2.257
	(4.52)	(3.00)
LEI Index	0.046	0.158
	(0.41)	(1.47)
Unexp GDP Growth	0.016	0.097
	(0.07)	(0.33)
Value Spread	8.861	0.279
	(0.80)	(0.02)
Small Value Spread	−2.288	3.432
	(−0.23)	(0.28)
Value DivYld − Growth DivYld	1.213	1.471
	(0.96)	(0.98)
1m HML Return	−0.021	0.034
	(−0.15)	(0.28)
Constant	−19.243	−31.517
	(−0.99)	(−1.76)
Adj. R^2	0.303	0.237
Years	35	35

onward at an annual frequency, we end up with annual IHD estimates from 1977 to 2011 for each occupation. We use these new hedging demand estimates to estimate our baseline 1-month-ahead regressions. We report the results in Table IX.

Given the findings in Davis and Willen (2000), we expect that electrical engineers, who have the most to gain from income hedging, should have an IHD that more closely replicates our main result than that of auto mechanics, who are unlikely to exhibit income hedging behavior. Consistent with this conjecture, we find that electrical engineers' IHD is a statistically significant predictor of HML returns, with a coefficient of −0.095 (t-statistic = −1.92). In contrast, auto mechanics' IHD is a statistically insignificant predictor of HML (coefficient = 0.054, t-statistic = 0.78).

B. Top Income Earners

Recent work by Guvenen et al. (2017) suggests that income hedging motives vary across households due to cross-sectional differences in exposure to aggregate risk. The authors show that those at the very bottom and very top of the income distribution are the ones who bear income risk, with respect to both aggregate GDP and their employer's earnings. In contrast, wage and salary earners with less income risk occupy the middle of the income distribution. Given that most market participants are at the top of the income distribution (Campbell et al. (2016)), the findings in Guvenen et al. (2017) suggest that the IHD of the top earners should have the most predictive power for returns.

We test this conjecture by examining how IHD measures stratified across income quantiles perform as HML predictors. Specifically, we use the Piketty and Saez (2003) top income growth data to calculate annual IHD measures for the bottom 90%, 91% to 95%, 96% to 99%, and top 1% of households in the income distribution. Since these data are available only at an annual frequency, we end up with 42 observations spanning the period 1970 to 2011. We substitute these group-specific IHD measures in our predictive HML regressions and report the results in Table X.

We find that the most important IHD predictors are those calculated using income growth for the 96% to 99% and top 1% of households. The respective coefficients for these groups are −0.208 (t-statistic = −2.25) and −0.187 (t-statistic = −1.93). In contrast, the IHD coefficients for the bottom 90% and 91% to 95% of households are economically smaller (−0.124 and −0.089, respectively) and insignificant (t-statistics of −1.48 and −1.08, respectively).

Given that the IHD estimates are negative on average (Table II), our results suggest that high income households should prefer growth over value stocks. In a recent study, Betermier, Calvet, and Sodini (2017) find that relatively young investors (i.e., between the ages of 35 and 55) favor growth stocks to value. We link the two sets of results by showing that relatively younger households are also the ones with the highest labor income. For this analysis, we extract the distribution of average labor income across age groups using age and income data from the CPS for the 1980 to 2017 period. We use the CPS because our IRS-based data set does not have demographic information. We find that the top earners are indeed relatively young (i.e., between the ages of 45 and 59), while older individuals (i.e., older than 70) belong mostly to the bottom of the income distribution.

Table X

Predictive Regression Estimates: Top Income Earners

This table reports coefficient estimates from regressions of the one-month-ahead HML return on income quantile-specific IHD estimates and a set of factor predictors, macroeconomic controls, and value factor predictors described in Table III. In columns (1) through (4), we compute IHD using the real annual income growth series of the top 1%, 96% to 99%, 91% to 95%, and bottom 90% of earners, respectively. These annual income growth series are from Piketty and Saez (2003). The estimation period is from 1970 to 2011. t-statistics computed using Newey and West (1987) adjusted standard errors are reported in parentheses below coefficient estimates.

Predictor, Month t	Top 1% (1)	96-99% (2)	91-95% (3)	Bottom 90% (4)
IHD	−0.187	−0.208	−0.089	−0.124
	(−1.93)	(−2.25)	(−1.08)	(−1.48)
RISK-RETURN	−0.133	−0.098	−0.102	−0.123
	(−0.92)	(−0.67)	(−0.64)	(−0.83)
DIV	−0.457	−0.370	0.343	0.037
	(−0.32)	(−0.25)	(0.21)	(0.02)
YLD	−0.092	−0.054	−0.235	−0.203
	(−0.22)	(−0.13)	(−0.50)	(−0.47)
TERM	1.214	1.287	1.009	1.072
	(2.55)	(2.61)	(1.90)	(2.18)
DEF	0.693	0.885	0.831	0.809
	(0.59)	(0.76)	(0.74)	(0.73)
Ind Prod Growth	−0.011	0.037	0.029	0.022
	(−0.03)	(0.11)	(0.08)	(0.06)
Inflation Rate	2.161	2.193	2.339	2.280
	(3.83)	(4.17)	(5.14)	(4.44)
LEI Index	−0.002	0.006	0.010	0.008
	(−0.02)	(0.09)	(0.13)	(0.11)
Unexp GDP Growth	0.302	0.293	0.305	0.301
	(1.65)	(1.58)	(1.79)	(1.71)
Value Spread	−2.590	−3.568	1.614	−0.605
	(−0.43)	(−0.57)	(0.26)	(−0.10)
Small Value Spread	0.386	1.718	−1.726	−0.582
	(0.07)	(0.31)	(−0.28)	(−0.10)
Value DivYld − Growth DivYld	1.443	1.422	1.263	1.339
	(1.47)	(1.49)	(1.23)	(1.33)
1m HML Return	0.067	0.066	0.054	0.065
	(0.42)	(0.42)	(0.35)	(0.41)
Constant	0.387	−1.938	−4.481	−2.298
	(0.04)	(−0.18)	(−0.36)	(−0.20)
Adj. R^2	0.390	0.405	0.345	0.361
Years	42	42	42	42

C. Labor Rigidities and Income Hedging

Recent literature suggests that income hedging motives might be less important because many firms insure their workers through labor contracts. Because such labor contracts shift some risk to stockholders, they end up affecting asset prices (Berk and Walden (2013), Marfè (2017)). We complement this recent work and argue that both hedging via labor contracts and financial markets can coexist.

To begin, it is important to consider the asset pricing implications of income hedging, since there is evidence that households consider income risk when making asset allocation decisions (e.g., Bonaparte, Korniotis, and Kumar (2014) and Betermier, Calvet, and Sodini (2017)). Guvenen et al. (2017) show that those at the very bottom and very top of the income distribution are the ones who bear income risk. In contrast, workers in the middle of the income distribution are more likely to be insured by their companies via labor contracts and do not bear much income risk. Consistent with this view, we show above that our results are driven mostly by the income risk of those at the top, and not the middle, of the income distribution.

Next, we present two additional tests that suggest hedging via labor contracts and financial markets can coexist. First, we consider the cross-sectional implications of firms insuring workers through labor contracts using the degree of unionization across states. Since unions typically advocate for rigid wage contracts (e.g., Shister (1943)), workers in areas with higher unionization rates should have a weaker motivation to self-insure in financial markets. To test this conjecture, we collect data on state-level unionization rates between 2000 and 2011. For each state, we calculate the average proportion of workers in the state who are union members. We then split our state-level panel into states with above- and below-median union representation. We estimate our baseline state-level regression with these two samples and report the results in Table XI.

We find that our main results hold in both subsamples. Specifically, in the presence of all baseline control variables, we find that IHD has a loading of -0.087 (t-statistic $= -2.21$) in the high-union-representation states and -0.125 (t-statistic $= -2.09$) in the low-union-representation states. Also consistent with the labor rigidity story, the IHD estimate is larger in the low-unionization sample. However, the difference between the two coefficients is not significant (Wald test p-value $= 0.593$).

In our second test, we compute the labor share measure of Marfè (2017) and include it as an additional control variable in our national-level HML predictive regressions. We report these expanded regressions in column (7) of Table XI. We find that in this expanded regression, IHD remains an economically and statistically significant HML predictor, with a coefficient of -0.170 (t-statistic $= -2.34$).

Taken together, our findings suggest that our main results are not subsumed by potential wage rigidities from firms insuring workers through their labor contracts. Instead, the findings of Guvenen et al. (2017) suggest that the results of Berk and Walden (2013) and Marfè (2017) are likely driven by firms insuring the income streams of workers in the middle of the income distribution. In contrast, our results seem to be driven by the income hedging motives of those at the top of the income distribution, a group that is subject to significant income risk.

Table XI

Predictive Regressions: State-Level Panel Union Representation and Aggregate Labor Share

This table reports estimates from within-state panel regressions of the one-month-ahead state-level HML return on state-level IHD measures. The state-level HML return is described in Table VI. The state-level IHD is based on conditional covariances between quarterly state income growth and national HML returns. In columns (1) to (3) ((4) to (6)), the sample consists of firms headquartered in states with above- (below-) median worker unionization rates. The estimation period is from Q1 1985 to Q4 2011. In column (7), the dependent variable is aggregate HML and we include the labor share of Marfè (2017) as an additional control. In column (7), the estimation period is from Q1 1970 to Q4 2011. t-statistics are reported below coefficient estimates. In columns (1) to (6), t-statistics are computed using standard errors adjusted for clustering at the state level. In column (7), t-statistics are computed using Newey and West (1987) adjusted standard errors.

	High Union Representation			Low Union Representation			Aggregate
Predictor, Month t	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IHD	−0.085	−0.094	−0.087	−0.110	−0.128	−0.125	−0.170
	(−2.64)	(−2.54)	(−2.21)	(−2.13)	(−2.31)	(−2.09)	(−2.34)
RISK-RETURN	−0.082	−0.082	−0.085	−0.047	−0.050	−0.060	0.056
	(−2.95)	(−2.53)	(−2.63)	(−1.13)	(−0.99)	(−1.14)	(0.88)
DIV		0.178	1.326		0.736	0.970	−0.055
		(0.34)	(2.53)		(0.88)	(1.01)	(−0.06)
YLD		−0.518	−0.531		−0.357	−0.362	−0.015
		(−4.11)	(−3.96)		(−2.61)	(−2.24)	(−0.09)
TERM		−0.320	−0.002		−0.063	0.065	0.321
		(−1.77)	(−0.01)		(−0.21)	(0.18)	(1.02)
DEF		1.557	1.655		0.738	0.917	(−0.220)
		(2.32)	(2.23)		(1.13)	(1.30)	(−0.28)
Ind Prod Growth		−0.295	0.096		−0.270	−0.039	0.186
		(−1.74)	(0.63)		(−1.75)	(−0.23)	(0.62)
Inflation Rate		0.398	0.391		0.451	0.507	0.904
		(1.89)	(1.65)		(1.05)	(1.17)	(1.99)

(Continued)

Table XI—*Continued*

	High Union Representation			Low Union Representation			Aggregate
Predictor, Month t	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LEI Index		0.011	0.073		0.047	0.071	−0.008
		(0.64)	(3.35)		(1.89)	(1.78)	(−0.17)
Unexp GDP Growth		0.418	0.293		0.347	0.280	0.169
		(6.75)	(4.96)		(5.95)	(4.27)	(1.37)
Value Spread		7.948	6.802		8.949	8.362	14.332
		(2.35)	(1.95)		(2.81)	(2.66)	(2.10)
Small Value Spread		−2.012	0.757		1.935	3.023	−8.844
		(−0.90)	(0.28)		(1.02)	(1.21)	(−1.71)
Value DivYld − Growth DivYld		1.538	1.589		1.499	1.524	1.039
		(8.30)	(7.78)		(5.00)	(4.56)	(2.16)
1m HML Return		0.016	0.016		−0.021	−0.015	−0.028
		(0.42)	(0.45)		(−0.47)	(−0.31)	(−0.22)
State Average Firm Size			−0.714			−0.368	
			(−2.15)			(−0.74)	
State Max Firm Size			0.015			0.004	
			(3.73)			(1.10)	
State Housing Growth			0.074			0.044	
			(1.21)			(0.83)	
Labor Share							−0.341
							(−1.09)
Constant							10.020
							(0.48)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	
Adj. R^2	0.005	0.055	0.052	0.003	0.050	0.047	0.100
U.S. States	17	17	17	18	18	18	
State-Quarter Observations	2,523	2,523	2,301	1,962	1,962	1,829	168

D. Additional Robustness Checks

Finally, in the Internet Appendix, we conduct additional tests to verify the robustness of our results with respect to the estimation of our IHD measure and the inclusion of additional control variables. Specifically, in Table IA.II, we consider alternative estimation windows for the IHD measure (8 to 15 years). In Table IA.III, we construct the IHD measure using different assumptions regarding the set of financial assets that are available to investors. In Table IA.V, we exclude some periods in which HML returns were extremely high or low. In Table IA.VI, we change the methodology of estimating hedging demand and use innovations from a VAR system to construct the IHD variable. In all four cases, IHD is a significant predictor of HML returns.

Furthermore, in Table IA.VII, we augment our baseline specification to control for income skewness, market effects captured by the market betas, and income growth volatility. We find that in the presence of these additional control variables, IHD remains a strong predictor of HML returns. In Table IA.VIII, we decompose the HML IHD into its value and growth components. The value (growth) IHD component is negatively (positively) related to future HML returns. Moreover, the value (growth) component of the HML IHD is negatively related to the value (growth) component of HML returns. Last, in Table IA.IX, we consider the IHD measures for the market, SMB, and UMD factors. The market IHD predicts market returns in our full sample. However, the IHDs for the SMB and HML factors predict the respective factor returns only in the later part of our sample. Overall, the evidence consistently supports our main finding that hedging demand-based measures are significant predictors of asset returns.

VII. Summary and Conclusion

This study examines the relation between income hedging and asset prices. Specifically, we investigate whether shifts in asset demand that are generated by income hedging motives can influence the prices of financial assets that facilitate income hedging. We focus on the income hedging potential of value and growth stocks and the pricing of the value-minus-growth portfolio, that is, the HML factor.

Since hedging demands are not directly observable, we propose a new method for estimating such demands for financial assets. Our proposed measure is based on the equilibrium of an economy with workers and sophisticated investors. Specifically, our IHD is the negative value of the covariance between asset returns and income scaled by the variance-covariance matrix of asset returns. Using our model-implied measure of income hedging, we show that systematic shifts in asset demands induced by income hedging motives affect the pricing of the HML portfolio in the short run. In economic terms, a one-standard-deviation decrease in IHD is associated with a 0.59% higher HML return next month.

We next exploit the geographic variation in income risk across the United States and show that state-level HML returns can be predicted using state-level estimates of hedging-induced demand shifts. A long-short portfolio that exploits this hedging-induced predictability earns an annualized risk-adjusted return of over 6% during the 1970 to 2011 sample period.

These findings can be extended along several dimensions. For tractability, our current study focuses on a set of standard financial portfolios, but our method can be generalized. Our hedging demand estimation framework can also be adapted to consider other types of risk such as real estate risk and entrepreneurial risk. In addition, it may be interesting to further exploit heterogeneity in income risk across different occupations and various demographic groups to obtain more accurate aggregate hedging demand estimates. We leave these interesting topics for future research.

Initial submission: December 9, 2015; Accepted: September 19, 2017
Editors: Bruno Biais, Michael R. Roberts, and Kenneth J. Singleton

Appendix A: Proof of Proposition 1

Let W_t^k be initial wealth, $\boldsymbol{\lambda}_{r,t}^k$ be an $n \times 1$ vector of holdings in the risky assets, which is expressed in number of shares, and $\lambda_{r_f,t}^k$ be holdings in the risk-free asset for $k \in \{wo(\text{rkers}), so(\text{phisticated investors})\}$. To prove Proposition 1, we first derive optimal asset demands for the two sets of investors. We then aggregate these demands imposing market clearing.

A.1. Sophisticated Investors

During the first period, sophisticated investors receive an endowment W_t^{so} that can be invested in the risky and risk-free assets. The first-period budget constraint for the sophisticated investors is

$$W_t^{so} = \lambda_{r_f,t}^{so} + \boldsymbol{\lambda}_t^{so\prime}\boldsymbol{p}_t + \frac{q}{2}\boldsymbol{\lambda}_t^{so\prime}\boldsymbol{\lambda}_t^{so},$$

where $\boldsymbol{p}_t$ denotes the vector of prices for the risky assets, and the last term captures the quadratic costs of investing in risky assets. By assumption, the price of the risk-free asset, whose supply is perfectly elastic, is one. The second-period budget constraint is

$$W_{t+1}^{so} = \lambda_{r_f,t}^{so}(1 + r_f) + \boldsymbol{\lambda}_t^{so\prime}(\boldsymbol{p}_{t+1} + \boldsymbol{d}_{t+1}),$$

where r_f is the interest on the risk-free asset and $\boldsymbol{d}_{t+1}$ is the vector of dividends for the risky assets. Solving the first-period budget constraint for $\lambda_{r_f,t}^{so}$, we can rewrite the second-period budget constraint as

$$W_{t+1}^{so} = W_t^{so}(1 + r_f) + \boldsymbol{\lambda}_t^{so\prime}\big(\boldsymbol{p}_{t+1} + \boldsymbol{d}_{t+1} - (1 + r_f)\boldsymbol{p}_t\big) - \frac{q}{2}(1 + r_f)\boldsymbol{\lambda}_t^{so\prime}\boldsymbol{\lambda}_t^{so}.$$

Since there is no intermediate consumption, the risk-neutral sophisticated investors maximize second-period expected wealth $\mathbb{E}_t^{so}[W_{t+1}^{so}]$ w.r.t. $\boldsymbol{\lambda}_t^{so}$. Following Gârleanu and Pedersen (2013), we define returns in excess of the risk-free rate as $\boldsymbol{r}_{t+1}^x = \boldsymbol{p}_{t+1} + \boldsymbol{d}_{t+1} - (1 + r_f)\boldsymbol{p}_t$. Thus, optimal portfolios for sophisticated investors are $\boldsymbol{\lambda}_t^{so} = \mathbb{E}_t^{so}[\boldsymbol{r}_{t+1}^x]/(q(1 + r_f))$. The expectation $\mathbb{E}_t^{so}[]$ is sophisticated investors' rational expectations operator, which reflects complete information.

A.2. Workers

Workers do not pay transaction costs when investing in risky assets. In addition to their first period endowment ($W_t^{wo} = y_t$), workers receive a second-period endowment y_{t+1}. Hence, the second-period budget constraint for workers is

$$W_{t+1}^{wo} = W_t^{wo}(1 + r_f) + \boldsymbol{\lambda}_t^{wo\prime}\boldsymbol{r}_{t+1}^x + y_{t+1}^{wo}. \tag{A1}$$

Let $\boldsymbol{z}_{t+1} = [\boldsymbol{r}_{t+1}^{x}{}' \; \Delta y_{t+1}]'$ be the $(n+1) \times 1$ vector of excess returns and income in first-differences, with $\mu_{z,t} = \mathbb{E}_t[\boldsymbol{z}_{t+1}]$ and $\boldsymbol{\Sigma}_{z,t} = Var_t(\boldsymbol{z}_{t+1})$ the conditional mean and variance of $\boldsymbol{z}_{t+1}$, respectively. We assume that workers form expectations using Bayes's rule. Also, to derive closed-form solutions for asset demands, we assume that workers believe that excess returns and income in first-differences are i.i.d. normal random variables with unknown parameters. Finally, workers have uninformative priors, which are given by $p(\boldsymbol{\mu}_{z,t}, \boldsymbol{\Sigma}_{z,t}) \propto |\boldsymbol{\Sigma}_{z,0}|^{-\frac{n+2}{2}}$ for some positive-definite and symmetric $(n+1) \times (n+1)$ matrix $\boldsymbol{\Sigma}_{z,0}$.

Under these assumptions, Zelner (1971) shows that the posterior distributions for $\boldsymbol{\mu}_{z,t}$ and $\boldsymbol{\Sigma}_{z,t}$ are: $\boldsymbol{\mu}_{z,t}|\boldsymbol{\Sigma}_{z,t}, \boldsymbol{z}_t \sim N(\widehat{\boldsymbol{\mu}}_{z,t}, \; \boldsymbol{\Sigma}_{z,t}/T)$, and $\boldsymbol{\Sigma}_{z,t}|\boldsymbol{z}_t \sim IW_{n+1}(T, T\widehat{\boldsymbol{\Sigma}}_{z,t})$, where $N()$ is the normal distribution and $IW_{n+1}()$ is the inverse Wishart distribution. Moreover, the estimates for the mean and variance of $\boldsymbol{z}_{t+1}$ are given by the following expressions:

$$\widehat{\boldsymbol{\mu}}_{z,t} = \widehat{\mathbb{E}}_t[\boldsymbol{z}_{t+1}] = \frac{1}{T}\sum_{\tau=t-T+1}^{t} \boldsymbol{z}_\tau, \quad \widehat{\boldsymbol{\Sigma}}_{z,t} = \widehat{Var}_t(\boldsymbol{z}_{t+1}) = \frac{1}{T}\sum_{\tau=t-T+1}^{t} (\boldsymbol{z}_\tau - \widehat{\boldsymbol{\mu}}_{z,t})(\boldsymbol{z}_\tau - \widehat{\boldsymbol{\mu}}_{z,t})'.$$

As shown above, the mean and variance estimates are based on the T most recent observations. In other words, workers in period t use data from $(t - T + 1)$ to t. The fact that workers use past observations to estimate return and income moments is an implication of the assumption that they are Bayesians with uninformed priors. Finally, according to Zelner (1971) and Klein and Bawa (1976), the standardized predictive distribution for $\boldsymbol{z}_{t+1}$, $p(\boldsymbol{z}_{t+1}|\boldsymbol{z}_t)$, is a multivariate t-distribution with $T - n - 1$ degrees of freedom and parameters $\widehat{\boldsymbol{\mu}}_{z,t}$ and $\frac{T+1}{T-n-1}\widehat{\boldsymbol{\Sigma}}_{z,t}$.

Workers are risk-averse and have identical quadratic preferences. We use quadratic utility so we can derive closed-form solutions for their asset demands. Following Avramov and Zhou (2010), the optimal Bayesian portfolio is obtained by maximizing expected utility under the predictive distribution

$$\max_{\boldsymbol{\lambda}_t^{wo}} \widetilde{\mathbb{E}}_t\left[W_{t+1}^{wo}\right] - \frac{\gamma}{2}\widetilde{Var}_t\left[W_{t+1}^{wo}\right], \tag{A2}$$

where $\widetilde{\mathbb{E}}_t$ and $\widetilde{Var}_t$ are the mean and variance under the predictive t-distribution, and W_{t+1}^{wo} is workers' wealth from equation (A1). In this case, the solution for $\boldsymbol{\lambda}_t^{wo}$ in equation (A2) is

$$\boldsymbol{\lambda}_t^{wo} = \frac{T-n-3}{\gamma(T+1)}\widehat{\boldsymbol{\Sigma}}_{r,t}^{-1}\widehat{\boldsymbol{\mu}}_{r,t} - \widehat{\boldsymbol{\Sigma}}_{r,t}^{-1}\widehat{\boldsymbol{\Sigma}}_{y,r,t},$$

where $\widehat{\boldsymbol{\Sigma}}_{r,t} = \widehat{Var}_t(\boldsymbol{r}_{t+1}^x)$ is the estimated covariance matrix of excess returns, $\widehat{\boldsymbol{\mu}}_{r,t} = \widehat{\mathbb{E}}_t[\boldsymbol{r}_{t+1}^x]$ is the vector of the estimated risk premia, and $\widehat{\boldsymbol{\Sigma}}_{y,r,t} = \widehat{Cov}_t(\boldsymbol{r}_{t+1}^x, \Delta y_{t+1}^{wo})$ is the vector of the estimated covariances between excess returns and income in first-differences.

A.3. Market Clearing

At any point of time, the new generation of sophisticated investors and workers buys the assets owned by the old generation. Therefore, when markets clear, the sum of the population-weighted asset holdings of the new generation is equal to the vector of the outstanding number of shares $\bar{\boldsymbol{N}}$, which is constant because risky assets are assumed to be in limited fixed supply. Formally, the market-clearing condition is given by $\bar{\boldsymbol{N}} = (1-\nu)\boldsymbol{\lambda}_t^{so} + \nu\boldsymbol{\lambda}_t^{wo}$. Replacing the expressions for optimal asset holdings, we get

$$\bar{\boldsymbol{N}} = \frac{1-\nu}{q(1+r_f)}\mathbb{E}_t^{so}\left[\boldsymbol{r}_{t+1}^x\right] + \frac{\nu(T-n-3)}{\gamma(T+1)}\widehat{\boldsymbol{\Sigma}}_{r,t}^{-1}\widehat{\boldsymbol{\mu}}_{r,t} - \nu\widehat{\boldsymbol{\Sigma}}_{r,t}^{-1}\widehat{\boldsymbol{\Sigma}}_{y,r,t}.$$

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Supporting Information

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Appendix S1: Internet Appendix.