Essays on Stock Investing and Investor Behavior

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Abstract

Chapter one shows that US households with high unconditional and cyclical labor income risk are more leveraged and allocate a greater share of their financial assets to stocks. I use self-reported risk preferences to show that rational sorting of risk tolerant workers into risky employment is responsible for this otherwise puzzling result. With risk preferences accounted for, I find evidence that households with greater permanent income variance reduce leverage and stock allocations to an extent consistent with theory. However, household portfolios and employment selection do not respond significantly to any of the other three forms of labor income risk I measure: disaster risk, permanent income cyclicality, and permanent income variance cyclicality.

Chapter two reports evidence that individual investors in Indian equities hold better performing portfolios as they become more experienced in the equity market. Experienced investors tilt their portfolios profitably towards value stocks and stocks with low turnover, but these tilts do not fully explain their performance. Experienced investors also tend to have lower turnover and disposition bias. These behaviors, as well as underdiversification, diminish when investors experience poor returns resulting from them, consistent with models of reinforcement learning. Furthermore, Indian stocks held by experienced, well diversified, low-turnover and low-disposition-bias investors deliver higher average returns even controlling for a standard set of stock-level characteristics.

Chapter three shows that news reflected by industry stock returns is only gradually incorporated into stock prices in other countries. Information links between cross-border portfolios play a significant role in explaining variation in the speed of this incorporation;

responses to industry news are rapid across borders where portfolios share more cross-listings, equity analyst coverage, and a greater common equity investor base. The drift in returns following cross-border industry news has halved in the past 25 years. About half of this change relates to a growth in information links and reductions in expropriations risks facing foreign investors. A simple long-short trading strategy designed to exploit gradual diffusion of industry news across borders appears profitable, but is unlikely to yield returns as high as the 8 to 9 percent annual rate the strategy has returned historically.

Contents

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Chapter 1

Why do Households with Risky Labor Income Take Greater Financial Risks?

1.1 Introduction

For most households, labor income is the greatest source of wealth, and a major source of risk. Does this labor income risk affect the financial risks that households take as theory suggests? The theoretical impact of labor income risk on household financial risks is not immediately apparent in US households. I show that employment characteristics associated with *greater* labor income risk are found among households that take *greater* leverage and allocate a *greater* share of financial assets to stocks. To understand this puzzle, I investigate how four forms of labor income risk are distributed across households, paying particular attention to the role of risk preferences.

First, I model labor income dynamics to identify these four forms of labor income risk and relate these risks to worker demographics and employment characteristics. I estimate this model using four decades of data from the Panel Study of Income Dynamics (PSID). In the second stage of my analysis, I use the Survey of Consumer Finances (SCF) to study how these demographics and employment characteristics further relate to financial risks and risk preferences. The labor income risks I study include the unconditional variance of permanent labor income (permanent income variance), the probability of becoming unemployed (as a proxy for disaster risk), the comovement of permanent labor income level and unexpected stock returns (permanent income cyclicality), and the comovement of permanent labor income variance and unexpected stock returns (variance cyclicality). I find economically and statistically significant variation across workers in each of these risks.

According to theory, exposure to these four labor income risks should affect the financial risks that households take. For example, Viceira (2001) shows that optimal stock allocations for workers with power utility fall in response to greater permanent income variance and permanent income cyclicality. Jacobson et al (1993) study the economic costliness of job loss, the likelihood of which can produce large changes in optimal portfolio allocations to risky assets (Bremis and Kuzin 2011). Mankiw (1986) and Constantinides and Duffie (1996) demonstrate the importance of variance cyclicality in asset pricing, with Lynch and Tan (2011) demonstrating implications for life-cycle variation in portfolio choice.

Labor income risks impact the optimal choice of household financial risks through two channels. These channels create the distinction between *unconditional* and *cyclical* risks.

The first channel by which labor income risk operates is through the effective risk tolerance of the household. Effective risk tolerance is the willingness of the household to take an additional risk, such as an investment in a volatile unhedged asset or by increasing leverage. Theory suggests that an investor's effective risk tolerance declines as the amount of uninsurable risk they face increases; the marginal costs of taking a risk increases with the total amount of risk.[1] I refer to labor income risks that decrease household effective risk tolerance by increasing background risk as *unconditional* labor income risks. The two unconditional labor income risks I measure are permanent (labor) income variance and the probability of becoming unemployed, which is a feasible measure of disaster risk.

The second channel by which labor income risk operates on optimal household stock allocations is through the desirability of stocks as a hedge; the covariance of the marginal

[1]Economic theory establishes that uncompensated background wealth risks decrease the willingness to accept independent gambles in conventional specifications of utility functions. For rigorous discussions of the generality and desirability of this, see Pratt and Zeckhauser (1987), Kimball (1993), and Gollier and Pratt (1996).

utility of wealth and stock returns. Risk averse households generally have greater marginal utility of wealth when wealth is low or highly uncertain.[2] Therefore, I measure two forms of *cyclical* income risk. Permanent income cyclicality measures the desirability of stocks due to covariation in permanent labor income level and unexpected stock returns. Permanent labor income variance cyclicality measures the desirability of stocks due to covariation in permanent labor income variance and unexpected stock returns.

My first main finding is that these unconditional and cyclical labor income risks are positively related with financial risks for households in the SCF. Controlling for household demographics and other sources of household wealth, such as home or private business ownership, does not explain this puzzle. Risk preferences remain the most promising explanation for the seemingly counter-theoretical relationships of labor income and financial risks.

The SCF provides a self-reported measure of willingness to accept financial risks, a proxy for risk tolerance. I use this measure to shed light on the relationship of labor income and financial risks. Past researchers have shown that this risk preference measure in the SCF is related to household stock investment.[3] I show that the SCF risk preference measure is also related to labor income risk.[4] For example, I show that households with greater permanent income variance, such as workers in business services industries or the self-employed, report significantly greater willingness to accept financial risks.

I investigate whether the relationships between labor income risks and risk preferences are coincidental or evidence of self-selection. I find that the positive relationship between permanent income variance and self-reported risk preferences relates to employment char-

[2]The marginal utility of wealth is also higher when disaster risk is greater, but it is very difficult to precisely estimate the heterogeneity in the covariance of workers' disaster risk and stock returns.

[3]For example, Bertaut and Starr-McCluer (2000), Vissing-Jorgenson (2002), and Curcuru et al (2010) relate the SCF risk preference measure to stock allocations. Brown, Garino, and Taylor (2012) link the PSID's self-reported risk preferences to debt accumulation.

[4]Guiso and Paiella (2005) and Bonin et al (2007) relate self-reported risk preferences in other datasets (the Italian Survey of Household Income and Wealth and German Socio-Economic Panel respectively) to income volatility and the variability of career outcomes. Saks and Shore (2005) relate background wealth to unexplained cross-sectional variation and volatility in occupational wages.

acteristics over which the household has significant control. In contrast, the relationship of the other three risks to self-reported risk preferences occurs primarily through worker demographics which are largely outside the household's control. This leaves doubt that aspects of labor income risk beyond permanent labor income variance enter meaningfully into employment decisions.

How does the endogenous distribution of risks affect conclusions about how households respond to labor income risks? To fully account for the role of risk preferences, I must deal with the measurement error in self-reported preferences. I use characteristics of the households, workers, and employment as instruments for the self-reported risk preferences. The instrumentation strategy assumes that employment characteristics (industry, occupation, and unionization and self-employment status) affect household stock allocations and leverage only indirectly through observed worker and household characteristics, labor income risks, and risk preferences.[5]

Once I account for household risk preferences, the puzzling relationships between labor income and financial risks disappear. Tobit regressions predict that a one-standard deviation increase in permanent income variance leads to an increase of 3.35% in household stock allocation when risk preferences are ignored. This changes to a 3.16% decrease once instrumented risk preferences are included as controls; a sign and magnitude consistent with theory. The impact of a one standard-deviation increase in permanent income variance on household leverage (debt-equity ratio) changes from 0.02 to -0.13 when controls for risk preferences are added, implying a 28% debt reduction for the typical household in the data.[6]

While I find evidence that households do respond to permanent income variance, I find no evidence that households adjust their stock allocations significantly in response to the other three labor income risks. I also find no evidence that the disaster risk (probability of

[5]I run a supplementary analysis motivated by Altonji, Elder, and Taber (2005) which suggests that the main results I obtain with this instrumentation strategy are robust to further omitted household characteristics.

[6]The full negative response of leverage and stock allocations to unconditional labor income risks is actually even larger to the extent that self-reported risk preferences already internalize household unconditional labor income risks. I discuss this issue further in Section 1.3.

job loss) affects household leverage. The lack of significant response of either financial risks or career choice to disaster risk may suggest that individuals are uncertain or unaware of their unemployment risk. The lack of portfolio response to the hedge-able cyclical labor income risks may additionally relate to narrow framing of risks. In order for households to respond optimally to their cyclical labor income risks, they must recognize and consider the statistical relationships between their labor income and stock returns. Such broad framing seems unlikely given that workers appear to miss out on substantial benefits of hedging labor income risks within their stock portfolios.[7]

This paper builds on previous research on how households adjust stock holdings in response to labor income risks.[8] Apart from demonstrating the importance of risk preference heterogeneity, I make three other contributions to the literature.[9] First, the set of unconditional and cyclical labor income risks I measure provides a more comprehensive description of the relevant aspects of labor income risk. Household responses to labor income disaster risk and variance cyclicality have not previously been studied. Secondly, I use a four decade time series and allow labor income to respond to unexpected stock returns with a lag. Both features are necessary to find the economically and statistically significant relationships between labor income and stock returns that might be expected.[10] Finally, I extend the analysis of household financial risks to consider leverage.

Section 1.2 of the paper describes the modeling, estimation, and distribution of the four labor income risks. Section 1.2 investigates the relationships between labor income risks, household financial risks, and self-reported risk preferences. Section 1.4 concludes.

[7] See Davis and Willen (2000) and Massa and Simonov (2006).

[8] A few examples are Guiso et al (1996), Heaton and Lucas (2000), and Angerer and Lam (2009). Two other papers look at shifts in household savings or portfolios around plausibly exogenous changes in labor income volatility to avoid bias due to endogenous distribution of labor income risks (e.g. Betermier et al (2012), or Fuchs-Schundeln and Schundeln (2005) for the role of precautionary savings).

[9] Schulhofer-Wohl (2011) demonstrates the importance of accounting for risk preferences in tests of risk sharing using consumption data.

[10] Most of the literature looks at the (weak) contemporaneous covariances between labor income growth, and uses short time windows to measure covariances. For example, see Vissing Jorgenson (2002) and Angerer and Lam (2009).

1.2 Modeling Labor Income Risks

1.2.1 Model of Labor Income Dynamics

This section provides a framework for estimating unconditional and cyclical labor income risks for households in the Survey of Consumer Finances (SCF). The SCF is an excellent dataset for measuring household financial risks, but it lacks the panel structure required to estimate labor income risk. Conversely, the PSID has a smaller cross-section and only rudimentary data on household financial risks, but it provides a four-decade panel data series on labor income and employment data. To use the strengths of both datasets, I develop a model which instruments the components of labor income risk using a set of worker demographics and employment characteristics, $CHAR$, which are found in both the SCF and the PSID. I then use the PSID to calibrate the model. This model is used in turn to estimate labor income risk for workers in the SCF as a function of their $CHAR$.

I start with a simple model of labor income dynamics described in Meghir and Pistaferri (2011). In this model, observed log labor income is characterized by a deterministic component, homoskedastic permanent shocks, temporary shocks which follow an MA(1) process, and measurement error. This is the simplest model which is able to adequately describe the variance of log labor income over both short and longer horizons. Permanent shocks are a useful feature as they are more easily interpreted in terms of their impact on welfare.

Equation (1.1) below is the adapted specification I use, expressed in terms of the observed labor income growth of worker i in year $t+1$, $g_{i,t+1}$.

$$\begin{aligned}\underbrace{g_{i,t+1}}_{\text{observed growth}} &= \underbrace{f(i,t)}_{\text{deterministic growth}} + \underbrace{\beta^{temp}(L)(i,t)(r_{t+1}-r_t) + \beta^{perm}(i,t)r_{t+1}}_{\text{cyclical labor income}} \\ &\quad + \Delta[\underbrace{e_{i,t+1}+\alpha e_{i,t}}_{\text{transitory shock}} + \underbrace{m_{i,t+1}}_{\text{measurement error}}] + \underbrace{\zeta_{i,t+1}}_{\text{permanent shock}} \end{aligned} \tag{1.1}$$

I add "cyclical labor income"to the basic specification that make the level of permanent labor income dependent on unexpected stock returns, r_t. These terms allow me to estimate permanent income cyclicality, the comovement of stock returns and the permanent part of log labor income. I now describe the terms in Equation (1.1) in more detail.

The first component, $f(i,t)$, represents expected changes in income that do not depend on stock returns. Individual variation in this deterministic labor income growth is fit by the vector of worker demographics and employment characteristics $CHAR_{i,t}$ as in Equation (1.2).

$$f(i,t) = \theta CHAR_{i,t} \tag{1.2}$$

$$CHAR_{i,t} = [\underbrace{\text{Educ}_i \ \text{Educ}_i \times \text{Age}_{i,t} \ \text{Other Demographics}_{i,t}}_{\text{Worker Demographics}} \ \text{Employment Characteristics}_{i,t}]$$

Worker demographics in $CHAR$ include age interacted with educational background at age 25 (high school dropout, graduate, or four-year college graduate), gender, race, marital status, and presence of children. Employment characteristics include occupation, industry, job tenure, and self-employment and unionization status. Deterministic labor income, $f(i,t)$, follows a quadratic hump-shaped pattern over the life-cycle, which is captured by the interacted age and education terms. Other terms in $CHAR_{i,t}$ are less important predictors of deterministic labor income growth.

Consider next the cyclical labor income terms from Equation (1.1). These terms are described by Equation (1.3) below. Variation in both terms is allowed through variation in $CHAR$.

$$\beta^{temp}(L)(i,t)(r_{t+1} - r_t) = \omega_0^{temp} CHAR_{i,t}(r_{t+1} - r_t) + \omega_1^{temp} CHAR_{i,t}(r_t - r_{t-1})$$

$$\beta^{perm}(i,t) r_{t+1} = \underbrace{\omega^{perm} CHAR_{i,t}}_{\text{permanent income cyclicality}} r_{t+1} \tag{1.3}$$

The combination of β^{temp} and β^{perm} terms allow unexpected stock returns, r_t, to have distinct temporary and permanent impacts on the level of log labor income. I model the temporary impact β^{temp} as an MA(1) for consistency with the MA(1) process assumed for the temporary shocks, e.[11] Since I work in terms of log labor income growth, the β^{temp} term appears in Equation (1.3) as an MA(1) in the change in unexpected stock returns.

[11] An MA(1) process is chosen to match the empirical autocorrelations of log labor income. For further discussion, see Meghir and Pistaferri (2011).

The permanent impact of stock returns on labor income $\beta^{perm} = \omega^{perm} CHAR$ is the measure of permanent income cyclicality I use. The term β^{perm} can also be thought of as the stock market beta of permanent log labor income, which is an approximation of the stock market beta of human wealth (present value of future labor income).[12] Stocks will tend to be especially unattractive investments for workers with high β^{perm}, whose lifetime earnings tend to fall at the same time as stocks do poorly.

Although β^{perm} is the risk measure of interest, β^{temp} terms are included in the model to allow log labor income to respond to unexpected stock returns differently in the short and long-run. This is quite important in practice, as the empirical relationship between labor income growth and stock returns appears much stronger when labor income is allowed to respond with a one year lag.[13]

The remaining three components of Equation (1.1) represent variation in log labor income growth not explained by deterministic growth rates or unexpected stock returns. The components $m_{i,t+1}$ and $e_{i,t+1} + \alpha e_{i,t}$ represent i.i.d. measurement error of log labor income and the MA(1) temporary shocks to log labor income. These terms are first differenced in Equation (1.1), which is stated in terms of log labor income growth rates rather than levels.

The third component is a serially uncorrelated term, $\zeta_{i,t+1}$, which represents shocks to permanent log labor income that are not explained by stock returns and therefore cannot be hedged with stock investment. The variance of this component, $\sigma^2(\zeta_{i,t+1})$, is modeled in

[12]Discrepancies between the stock market beta of permanent log labor inomce and human wealth are likely to be modest and arise from (1) the fact that human wealth is also affected by temporary fluctuations in labor income and (2) changes in the discount rate (due to changes in relative wealth and background risk) which also affect the individual's human wealth. For a detailed discussion of the discount rate on worker-specific human wealth, see Huggett and Kaplan (2012).

[13]In the PSID, the correlation of aggregate labor income growth and contemporaneous unexpected stock returns is only 0.08, but the correlation of aggregate labor income growth and the past year's unexpected stock returns is 0.53. The lagged response of labor income is also pointed out by Campbell et al (1999) and Campbell and Viceira (2002).

Equation (1.4) below.[14]

$$E_t[\sigma^2(\zeta_{i,t+1})] = \underbrace{\phi CHAR_{i,t}}_{\text{permanent income variance}} + \underbrace{\psi CHAR_{i,t}}_{\text{variance cyclicality}} r_t \tag{1.4}$$

The variance of ζ is decomposed into unconditional permanent income variance and variance cyclicality, with both parts instrumented by $CHAR$ as usual. Variance cyclicality is defined as the change in the cyclical part of permanent income variance predicted by the past year's unexpected stock returns.[15] Negative variance cyclicality (i.e. variance counter-cyclicality) makes stocks a less attractive investment, as poor stock returns predict greater uncertainty in permanent income, increasing precautionary savings and the marginal utility of wealth. High unconditional permanent income variance should make extra financial risk, in the form of stocks or greater leverage, less attractive.

The permanent shocks ζ are not observed, but they can be identified. Since the temporary part of labor income growth, $\Delta[e_{i,t+1} + \alpha e_{i,t} + m_{i,t+1}]$, has two lags, the temporary component of labor income growth over the period $t-1$ through $t+3$ is uncorrelated with ζ_{t+1}. As a result, permanent income variance and variance cyclicality can be identified using Equation (1.5).

$$E[\zeta_{i,t+1}^2] = E[\tilde{g}_{i,t+1} \sum_{k=-1}^{3} \tilde{g}_{i,t+k}] \tag{1.5}$$

$$\text{where} \quad \tilde{g}_{i,t+1} = g_{i,t+1} - \big(f(i,t) + \beta^{temp}(L)(i,t)(r_{t+1} - r_t) + \beta^{perm}(i,t)r_{t+1}\big)$$

The probability of disaster outcomes is an important aspect of labor income risk to capture, as it can have a drastic impact on effective risk tolerance.[16] There is no reason to expect that permanent income variance is a good proxy for the cross-sectional variation

[14] I do not model the variance of temporary shocks for two reasons. First, temporary shocks to labor income, which last only a year or two, should be less economically important than permanent shocks to labor income are. Second, identifying the variance of temporary labor income shocks in the presence of measurement error requires further assumptions.

[15] A one-year lag of returns is used since stock returns primarily impact log labor income with a one-year lag; the change in permanent income variance associated with r_t is likely realized by the worker in t though it only appears to the econometrician in $t+1$.

[16] See, for example, Cocco, Gomes, and Maenhout (2005).

in the left tail of permanent labor income shocks (i.e. disasters), so a separate measure is required. In principle, I could estimate higher moments of ζ, such as skewness. However, cross-sectional variation in higher moments cannot be estimated precisely unless the data have a very large cross-sectional dimension.[17] As a viable alternative disaster risk measure, I estimate the probability that a worker becomes unemployed using the specification given by Equation (1.6) below.

$$\Pr[\text{Becomes Unemployed in } t+1] = z_t \underbrace{\left(\mu CHAR'_{i,t}\right)}_{\text{disaster risk}} \tag{1.6}$$

The z_t in Equation (1.6) reflects annual macroeconomic shocks, which I assume affect each worker's probability of job loss proportionally. Variation in the unconditional probability of job loss is modeled by $CHAR'$, which is equal to $CHAR$ with the self-employment dummy removed. It is difficult to interpret job loss for the self-employed, so I exclude them from the estimation of Equation (1.6).

Comments on the Model

Although the model I adapt is standard, it is worth considering how the modeling assumptions shape estimates of the labor income risks. One of the most actively debated areas in modeling labor income dynamics is whether or not (log) labor income has a unit root. Evidence in favor of a unit root is generally quite strong unless individual-specific variation in income growth is allowed for, in which case results are mixed.[18] If the permanent income shocks, ζ, are replaced by a persistent autoregressive process, this persistent process adopts the cyclical growth and variance otherwise attributed to permanent income shocks. While comparably sized shocks to a autoregressive process are less economically important (and

[17]One such cross-sectional investigation is by Guvenen et al 2012, who explore the distribution of income changes over economic upturns and downturns using a very large administrative database.

[18]See Meghir and Pistaferri (2011) for further discussion. To allow greater heterogeneity in income growth rates, I have experimented with expanding the set of PSID variables used to fit deterministic labor income growth rates, such as self-reported employment problems the worker has had or is likely to experience, housing cost-income ratios, and survey measures of workers' aspirations and ambitions. Adding these variables has little effect on the estimated labor income risks.

harder to interpret) than comparably sized permanent shocks, relative comparisons of risks between workers remain largely unchanged.

However, even if the dynamics of the true labor income process do have a unit root, the permanent labor income variance I estimate should be interpreted with caution.[19] The worker may have information that allows them to forecast their future labor income better than the econometrician so that the variance of ζ I estimate is too large.[20] However, as with the issue of shock persistence, if workers have superior information, the "permanent"income shocks are less economically important than they appear, but comparisons of permanent income variance across workers should still be valid.

1.2.2 Estimation of Labor Income Risks from the Model

I use panel data from the "Core Sample"of the PSID to estimate the labor income models in the last section.[21] These data cover labor income growth g, and worker demographics and employment characteristics $CHAR$ of household heads over the period 1968 through 2008. I cannot use spousal labor income to fit the model since the PSID contains less complete data on the characteristics of spousal employment. I include workers in the analysis only if they are in the labor force and between the ages of 25 and 60. This minimizes the role of transitions around education and retirement decisions. I detail further data screens and discuss how labor force status (employed, unemployed, or not in the labor force) is determined in Appendix A.1. The resulting cross-sectional dimension of the data used varies from 2,032 to 4,082 workers.

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[19] The worker's superior information set does not bias the estimates of permanent income cyclicality or variance cyclicality, since the worker's information would need to also predict future unexpected stock returns.

[20] Evidence of this superior information is suggested by the lower levels of variance in consumption growth data and self-reported income uncertainty measures (e.g. Italian SHIW data), and predictability of income growth from the household choices of consumption commitments such as housing. See also Guvenen and Smith (2010), who use household consumption-savings data to argue that lifetime labor income appears far less risky to workers than it does to the econometrician.

[21] The Core Sample consists of a representative sample (Survey Research Center Sample) and a supplemental oversampling of lower income and minority households (Survey of Economic Opportunity Sample). The PSID's composition changes in 1997 when coverage of about half of the SEO sample is discontinued and a relatively small supplement of immigrant households is introduced.

I include unemployment insurance and workers' compensation payments in labor income. Income and all other monetary amounts throughout the paper are expressed in constant 2009 US Dollars using the "all items, all urban consumers"price index from the Bureau of Labor Statistics.

Table 1.1 provides summary statistics for most recent wave of the PSID that I use. The set of household heads from which labor income risks can be estimated has a similar distribution of age, job tenure, income, and educational background as the greater universe of household heads.

Table 1.2 provides the joint distribution of workers across industry and occupation categories. The particular classification of industries and occupations I use matches the classification in the Survey of Consumer Finances (SCF) so that the instrumented labor income risks can be fit to workers in the SCF. The "agriculture and forestry"industry and "farmer, forester, and animal related"occupation category are extremely similar so I reclassify a few workers to make the categories equivalent. Otherwise, workers in each industry have representation across all occupations.

To measure cyclical risks, I construct a measure of unexpected stock returns, r_t. I start with the value-weighted US excess stock return from Ken French's website. To remove the expected part of the excess stock return, I take the residual from a regression of the excess return over the period 1927 through 2011 on one-year lagged excess stock returns and Robert Shiller's cyclically-adjusted price-earnings ratio. Annual unexpected stock returns over the period 1968 through 2008 vary between -44.2% in 1974 and 32.5% in 2003.

The PSID has been conducted biennially since 1997. To make use of the entire time-series, I modify Equations (1.1), (1.4), and (1.5) slightly to make use of observations of log labor income growth over two-year periods. Specifically, I use Equations (1.7) and (1.8) below to estimate three of the four labor income risks. These equations result from combining Equations (1.1), (1.2), and (1.3) and Equations (1.4) and (1.5) respectively, and then summing

Table 1.1: *Summary Statistics: Working Heads in the PSID (2009 Wave)*

PSID sampling weights are used to produce statistics in this table. Labor income is expressed in CPI adjusted 2009 dollars and is computed only for the subset of workers who are currently employed.

	All Working Heads, Age 25 to 60				Heads Used in Risk Estimation			
Number of Households	5,181				3,898			
		Percentiles				Percentiles		
	Mean	10th	50th	90th	Mean	10th	50th	90th
Age	42.7	28.0	43.0	57.0	44.6	31.0	45.0	57.0
Head is Male	81.7%				76.9%			
White	74.0%				83.7%			
High School Dropout	7.8%				7.2%			
High School Graduate	59.1%				59.9%			
BA Degree or Above	33.1%				32.9%			
Married	50.4%				56.2%			
Has Dependent Child	40.2%				41.0%			
Head Labor Income (in 2008)	$66,017	$19,107	$47,831	$119,576	$69,777	$20,551	$49,824	$121,569
Job Tenure (Years)	8.0	0.5	4.5	22.0	8.8	0.5	5.0	23.5

Table 1.2: *Distribution of Workers Across Industry and Occupation Groups*

The distribution of workers across industry and occupation groups is computed for each wave of the PSID using sampling weights. The distribution above is the average of these yearly estimates. I omit 3.1% of workers who are classified in the "agriculture or forestry"industry. Due to the almost perfect overlap of this industry category with the "farmer, forester, or animal related"occupation category, I reclassify a few workers so that the two are equivalent.

	Occupations				
Industries	Professionals	Clerical, Sales, Technicians	Service Workers	Maintenance and Assembly	Equipment Operators
Mining and Construction	2.8%	0.5%	0.2%	5.7%	0.8%
Manufacturing	4.7%	2.0%	0.5%	4.6%	5.7%
Trade	7.0%	5.8%	1.5%	2.6%	4.0%
Business Services	5.1%	3.2%	0.5%	1.3%	0.3%
Utilities, Personal Services	15.0%	4.9%	5.0%	3.0%	2.5%
Public Administration	2.7%	1.7%	2.4%	0.5%	0.7%

over two consecutive years.

$$\begin{aligned}E[g_{i,t+2}+g_{i,t+1}] =& \theta(CHAR_{i,t+1}+CHAR_{i,t})+\omega_0^{temp}[CHAR_{i,t+1}(r_{t+2}-r_{t+1})+CHAR_{i,t}(r_{t+1}-r_t)]\\ &+\omega_1^{temp}[CHAR_{i,t+1}(r_{t+1}-r_t)+CHAR_{i,t}(r_t-r_{t-1})]\\ &+\omega^{perm}(CHAR_{i,t+1}r_{t+2}+CHAR_{i,t}r_{t+1}) \qquad (1.7)\end{aligned}$$

$$E[(\tilde{g}_{i,t+2}+\tilde{g}_{i,t+1})[\sum_{k=-1}^{4}\tilde{g}_{i,t+k}]] = \phi(CHAR_{i,t+1}+CHAR_{i,t})+\psi(CHAR_{i,t+1}r_{t+1}+CHAR_{i,t}r_t) \qquad (1.8)$$

$$\text{where} \quad \tilde{g}_{i,t+1} = g_{i,t+1}-\big(f(i,t)+\beta^{temp}(L)(i,t)(r_{t+1}-r_t)+\beta^{perm}(i,t)r_{t+1}\big)$$

Given worker demographics and employment characteristics $CHAR$, the estimated coefficients ϕ (Equation (1.8)), μ (Equation (1.6)), ω^{perm} (Equation (1.7)), and ψ (Equation (1.8)) determine a worker's permanent income variance, disaster risk, permanent income cyclicality, and variance cyclicality respectively. Equations (1.7) and (1.8) are estimated by least squares with each cross-section (year) weighted so that it receives equal weight in the estimation.[22] Equation (1.6) is first estimated cross-sectionally. As a second step, classical minimum distance estimation is used to estimate coefficients μ and the macroeconomic scaling factors z_t. All estimates make use of PSID sampling weights in the cross-section.[23]

Table 1.3 provides summary statistics describing cross-sectional variation in each of the four labor income risks across workers in the PSID. Time-series variation in the risk measures is suppressed by setting r_t and z_t equal to their time-series averages. The last two columns of Table 1.3 provide the labor income risks for two hypothetical demographically identical workers, one with high risk employment as a self-employed general building contractor (worker A) and the other with low risk employment as a unionized postal worker (worker B).

The building contractor has 70% greater permanent income variance and significantly

[22] Years where the survey is annual (through 1996) are assigned half as much weight since these observations are otherwise double-counted when using two-year periods as the basis for estimates.

[23] The PSID sampling weights result from (1) variations in PSID response rates and (2) oversampling of low income households in the Survey of Economic Opportunity part of the sample.

Table 1.3: *Summary Statistics - Labor Income Risks*

Statistics are produced for the set of worker-years used for the risk estimation. Weights are set within each year so as to be representative of the broader population of household heads, and set across years to equalize the total weight received by each two-year period. Permanent income variance (counter) cyclicality is measured here as 100 times the change in variance per negative one standard deviation of unexpected stock returns. I remove the time-series variation in permanent income variance and disaster risk due to r_t and z_t by replacing these values with their time-series averages. Workers (A) and (B) are both 40-year old married white male high-school graduates with two children and 10 years job tenure. Worker (A) is a self-employed general building contractor. Worker (B) is a unionized postal worker. Worker (A)'s self-employment status does not affect the estimate of A's disaster risk since disaster risk (probability of job loss) is estimated on data that excludes self-employed workers.

Worker-Year Observations	**Mean**	**Median**	**Std Dev**	**Worker (A)**	**Worker (B)**
100 X Permanent Income Variance ($\sigma^2(\zeta)$)					
62,009	2.25	2.26	1.11	2.35	1.38
Disaster Risk (Job Loss)					
71,991	2.77%	2.58%	2.18%	3.41%	0.66%
Permanent Income Cyclicality (Stock Market Beta β^{perm})					
103,810	0.115	0.114	0.066	0.243	0.085
Permanent Income Variance (Counter) Cyclicality					
62,009	0.13	0.06	0.73	1.58	0.16

greater disaster risk as compared to the postal worker.[24] The contractor's permanent income level moves three times as strongly with the stock market, equating to $160,000 of extra stock market exposure if the value of the contractor's future labor income, i.e. human wealth, is $1 million. Finally, only the building contractor faces much higher permanent income variance following poor stock returns.

To show how this variation is spread across workers more generally, Figure 1.1 plots the average of each type of labor income risk for workers sorted by demographic and employment characteristics. The two unconditional risks are shown in the part (a) plots and the two cyclical risks in the part (b) plots. Colored bars and bold type distinguish where the sorts produce statistically significant variation based on a block bootstrap (Hall and Horowitz 1996).

The last two sorts in Figure 1.1 compare the labor income risks with two measures of income cyclicality. Occupation and industry wage betas are the coefficients from regressions of occupation and industry-specific wage growth on aggregate wage growth. Employment industry stock beta is the stock market beta of the portfolio which holds stocks from the worker's industry of employment. The construction of these characteristics is detailed further in Appendix A.2.

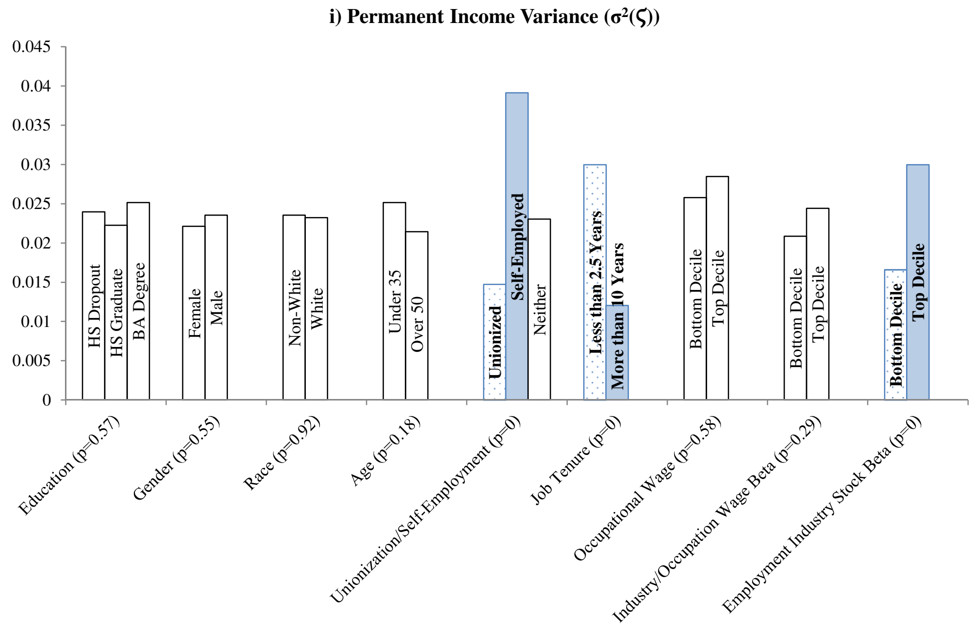
Table 1.3 shows that unconditional permanent log labor income variance averages around 0.02 and generally varies between about 0.008 and 0.04, corresponding to a range of standard deviations of 9 to 20 percent. In contrast, the standard deviation of annual aggregate real log labor income growth is less than three percent. However, the worker's own permanent labor income variance is lower than my estimate to the extent that the worker is able to produce a superior forecast of their own labor income.

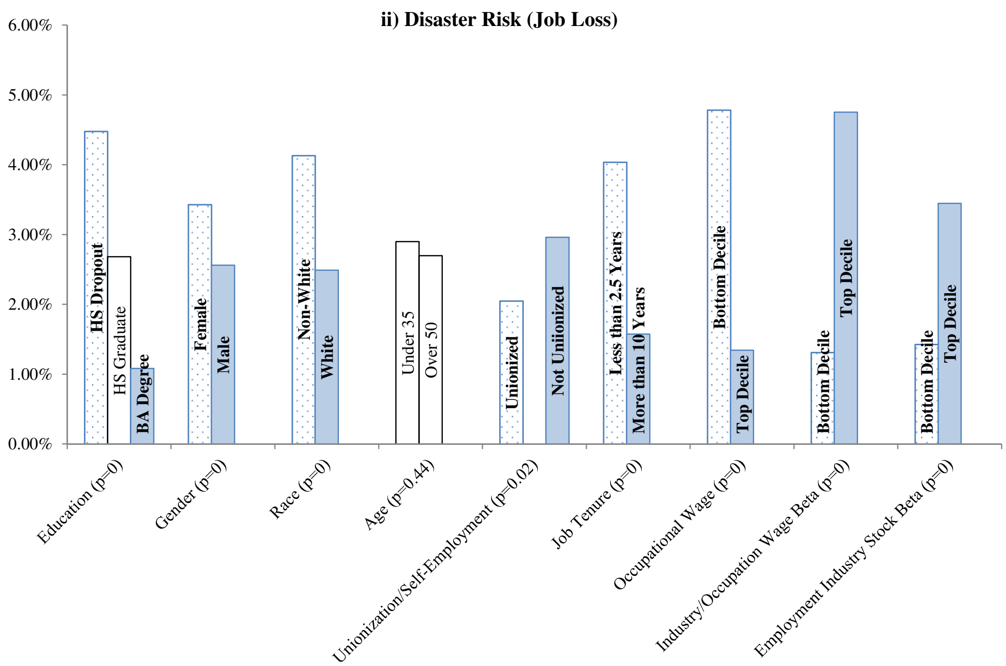
Figure 1.1 shows that very little of the cross-sectional variation in permanent income variance is related to worker demographics, but employment characteristics are quite important. Permanent income variance is larger for recently hired employees and the

[24] Disaster risk (probability of becoming unemployed) is not computed for self-employed workers, so worker A's estimated disaster risk is not conditional on his self-employment status (estimated using $CHAR'$, not $CHAR$).

Figure 1.1: *Labor Income Risks*

(a) *Unconditional Risks*

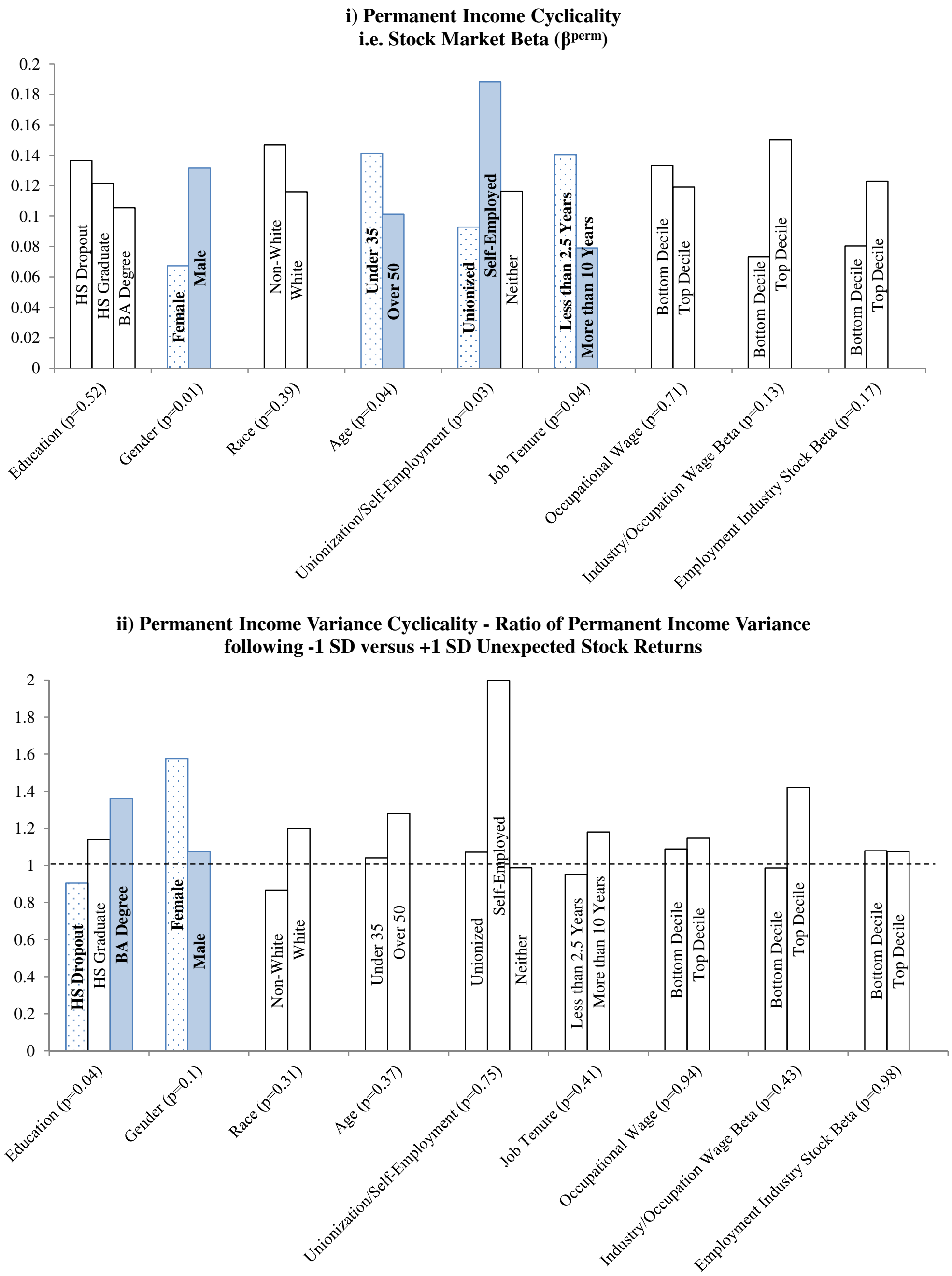




The labor income risks are computed as the average (using sampling weights) by group, where the groups are formed by sorts on worker demographics and employment characteristics. Time-series variation due to r_t and z_t is removed by replacing these values with their time-series averages when constructing the fitted values. *Continued on next page.*

Figure 1.1: *(Continued) Labor Income Risks*

(b) *Cyclical Risks*



Continued. For interpretive ease, the permanent income variance cyclicality is given here as the ratio of the estimated permanent log labor income variance following a negative one-standard deviation unexpected stock market return to the variance of the same following a positive one-standard deviation unexpected stock market return. Statistically significant differences (two-sided 10% level or better) are indicated by shaded bars and bold type, and is determined by bootstrap of disjoint three-year blocks of data.

self-employed, who have permanent log labor income variance about three times as great as that of employees with long job tenure or who are unionized. Permanent income variance is also positively related to wage and industry stock betas.

Labor income disaster risk, the probability of becoming unemployed, typically varies from about one to four percent in the cross-section. The mean is just below three percent. These numbers are lower than unemployment rates since it sometimes takes more than one year to retain employment once unemployed.[25] As with permanent income variance, the risk of job loss is greater for less tenured, non-unionized workers, and workers in cyclical (high stock beta) industries. However, demographics also predict the probability of becoming unemployed. Less educated workers and workers who are in low wage occupations or are racial minorities, face a greater likelihood of becoming unemployed.

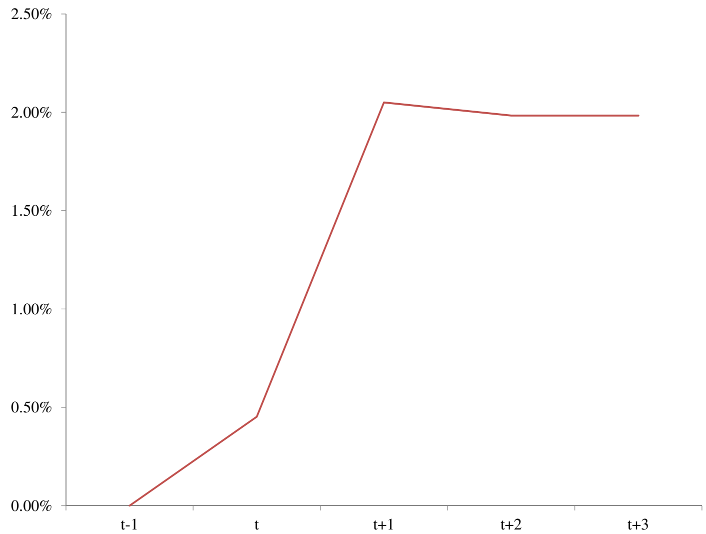
The average permanent income cyclicality, or permanent income stock beta, is about 0.115. This implies that log labor income typically increases permanently by about two percent for each standard deviation of annual unexpected stock returns. Figure 1.2 uses the fitted temporary (driven by β^{temp}) and permanent (driven by β^{perm}) parts of the log labor income response to show that the majority of the response does not appear until after a one year lag.[26] Allowing further lags in the temporary response of labor income to stock returns does not significantly change the magnitude of the estimated permanent response.

Most workers have permanent income stock betas between about 0.03 and 0.20, which is a large enough range to make a significant difference in the composition of optimal financial portfolios, as the example of workers (A) and (B) illustrates. Part (b) of Figure 1.1 shows that younger (0.14) and male (0.13) household heads have significantly higher labor income stock betas than older (0.10) and female (0.07) household heads. Self-employed workers have much higher labor income stock betas (0.19). Labor income betas are almost twice as high for workers with little job tenure as for those with a decade or more job tenure

[25]Cross-sectional variation in estimates of the probability of being unemployed is very similar to the cross-sectional variation in the estimates of the (smaller) probability of becoming unemployed that I use.

[26]This is similar to the finding in Campbell and Viceira (2002).

Figure 1.2: *Average Response of Log Labor Income to a Positive One-Standard Deviation Unexpected Stock Market Return in Year t*



The plotted series is the population average fitted response of log labor income to a positive one standard deviation (16.63%) unexpected stock market return. The coefficients used to generate the plot are the average fitted β^{temp} and β^{perm} from Equation (1.1).

(0.14 versus 0.08). Wage beta and employment industry stock beta predict economically significant variation in betas, though this difference is not highly statistically significant.

The fourth risk in Table 1.3 is variance (counter) cyclicality, the change in permanent log labor income variance predicted by a negative one-standard deviation unexpected stock return in the prior year. Permanent income variance is typically only modestly counter-cyclical, increasing only a few percent following the negative one standard-deviation return. However, permanent income variance appears to be far more counter cyclical for a few workers, such as the self-employed building contractor.

The final plot of Figure 1.1 presents the cross-sectional variation in variance cyclicality by dividing each group's average permanent income variance following bad unexpected stock returns by the average such variance for the group following good unexpected stock returns. The most robust result is that permanent income variance is counter-cyclical primarily for more educated workers. The cyclicality of variance is hard to estimate, and results based on

Table 1.4: *Cross-Sectional Correlation of Labor Income Risks*

Notes to Table 1.3 describe the labor income risks used and weighting scheme. The correlations are computed in a weighted pairwise manner using all worker-years used in the estimation.

		[1]	[2]	[3]	[4]
Permanent Income Variance ($\sigma^2(\zeta)$)	[1]	1.000	0.424	0.479	0.186
Disaster Risk (Job Loss)	[2]		1.000	0.459	0.190
Permanent Income Cyclicality (Stock Market Beta β^{perm})	[3]			1.000	0.187
Permanent Income Variance (Counter) Cyclicality	[4]				1.000

the other sorts show low statistical significance levels as a result.[27]

Table 1.4 provides a cross-sectional correlation of the four labor income risks. The correlations between permanent income variance, labor income disaster risk, and permanent income cyclicality (stock beta) are all substantial, between 0.42 and 0.48. This is not surprising given that all three point towards greater risks for workers with short job tenure, self-employment, high wage beta, and high stock beta in the industry of employment. The lower correlations of the cyclicality of the variance with the other labor income risks is due in part to the difficulty in precisely measuring this risk.

Use of a long time-series is necessary to estimate cyclical labor income risks; four decades of data still only represent a handful of business cycles. However, four decades may be long enough for the distribution of labor income risks across the population to change. To investigate this possibility, I re-estimate unconditional labor income risks using only the last decade of data. Overall, the distribution of risks looks reassuringly similar, with the relative riskiness of industries and occupations unchanged. The largest discrepancy is that self-employed workers appear to have modest permanent income variance in the past

[27] Storesletten, Telmer, and Yaron (2004) use cross-sectional wage dispersion within cohorts to identify variance cyclicality with out of sample data (past business cycles). However, I cannot use this technique to gain statistical power since I model variance as dependent on time-varying employment characteristics (which are not observed prior to the start of the PSID).

decade, though there is not enough data to say that this recent difference is statistically significant.

1.3 The Relationship of Labor Income Risks, Household Portfolios, and Risk Preferences

1.3.1 How Financial and Labor Income Risks are Distributed

Variation in labor income risks should predict variation in household financial portfolios, provided that households are aware of these risks and respond as theory suggests. Permanent income variance and disaster risk represent major background risks to household budgets. Greater levels of these unconditional risks should decrease the household's effective risk tolerance, discouraging leverage or holdings of volatile, non-hedged assets. The two cyclical labor income risks relate to the covariance of marginal utility of wealth and stock returns; payoffs on stock are more valuable when labor income declines or its variance increases. For most workers, permanent labor income falls and its variance rises following unexpected declines in the stock market. This statistical relationship makes stocks less attractive than they would be if stock returns and labor income were independent.[28] However, stocks exacerbate risks to wealth even more for workers who are younger, self-employed, and in cyclical industries.

I use data on household financial portfolios from the Survey of Consumer Finances (SCF) to investigate how labor income risks relate to actual household portfolios. I use the 2004, 2007, and 2010 waves of the SCF, as these most recent waves of the survey provide specific accounting for the share of mutual funds and retirement plan assets invested in stocks.[29] As

[28] I treat stocks as a diversified investment in the US stock market, but households may be able to form better hedges against their labor income fluctuations using individual stocks. This discrepancy is not a concern as long as the household's permanent labor income stock market beta is a good proxy for the household's ability to hedge with an optimal stock portfolio. Furthermore, it seems unlikely that many households would have the financial sophistication or will to spend the effort to form such "hedge"portfolios from individual stocks. Massa and Simonov (2006) suggest they do not.

[29] Earlier waves of the SCF indicate only if a retirement plan or mutual fund was fully, partially, or not at all invested in stocks.

with the PSID dataset, I restrict analysis to households whose employed head and spouse have an average age between 25 and 60.[30] Self-reported expectations of years to retirement are reported in the SCF, so I also exclude households where the average time to retirement is less than two years. Further data screens and the construction of variables from SCF data are discussed in Appendix A.3.

Although the SCF does not provide data on the dynamics of household labor income, it does provide demographic and employment characteristic data $CHAR$ for working household heads and spouses. To estimate labor income risks for workers in the SCF, I fit the $CHAR$ of workers in the SCF to the instrumented labor income risks estimated using PSID panel data in the last section.

In SCF households where only the head or spouse is part of the labor force, I equate household level labor income risks with the worker specific labor income risks. However, both the head and spouse are in the labor force in about 50% of SCF households, with the secondary income earner accounting for an average of 32% of household human wealth. Where head and spouse both work, I construct the household level disaster risk and permanent income cyclicality as the weighted average of these risks for the head and spouse, using each worker's share of household human wealth as weights.[31] I approximate the variance of household-level permanent log labor income as $\sigma^2(\zeta_{hhold}) = w_{head}^2\sigma^2(\zeta_{head}) + w_{spouse}^2\sigma^2(\zeta_{spouse})$, where the w_{head} and w_{spouse} are the head and spouse share of household human wealth. This is only an approximation as it assumes that $\zeta_{hhold} = w_{head}\zeta_{head} + w_{spouse}\zeta_{spouse}$ and that ζ_{head} and ζ_{spouse} are uncorrelated.[32] Similarly, I estimate the response of household-level permanent log labor income variance to stock returns as $w_{head}^2\hat{\psi}_{head}CHAR_{head} + w_{spouse}^2\hat{\psi}_{spouse}CHAR_{spouse}$, where $\hat{\psi}_{head}CHAR_{head}$ represents

[30]In all instances of averaging demographic attributes across the (possibly) two working members of a household, the attributes of household workers are weighted by the worker's share of household human wealth. The estimation of human wealth is discussed in Appendix A.4.

[31]Admittedly, job loss is less of a disaster where another worker in the household remains unemployed. To help deal with this, I include a control for the concentration of household labor income in subsequent analysis.

[32]Household level permanent log labor income shocks only approximately equal the given weighted sum of head and spouse permanent log labor income shocks. Head and spouse permanent labor income shocks ζ have a small positive correlation (0.06) in the PSID.

the response of the head's permanent log labor income variance to stock returns.

Many households have extremely limited financial assets.[33] Even modest participation or attention costs would be sufficient to keep such households from investing in stocks or optimizing portfolio allocations. I restrict attention to households for which financial portfolio adjustments could significantly respond to labor income risks and have non-trivial welfare implications. To do this, I exclude households with financial assets worth less than one tenth of their human wealth, the present discounted value of future labor income.[34] Estimating human wealth is a non-trivial task involving estimates of income trajectories, self-reported retirement expectations, and selection of a discount rate that appropriately accounts for the uninsurable risk that labor income represents.[35] Details of the human wealth estimation are covered in Appendix A.4. After excluding households with relatively modest financial assets, very few households where the head or spouse are high-school dropouts remain, so I exclude these potentially aberrant households from the sample.

Relatively few young households have accumulated sufficient financial assets relative to their human wealth to be included in the sample. To deal with concerns that these households may be atypical in other ways, I include controls for age and financial assets relative to human wealth in the following analysis. Furthermore, the relationships that I will show exist between labor income risks, stock allocations, and leverage weaken a bit but remain sizable when households with limited financial assets relative to human wealth are not excluded from analysis.[36] Some attenuation of results should be expected. For

[33]According to the 2010 SCF, 37% of US households have less than $10,000 in financial assets, including employer and individual retirement plans. Financial assets exclude property and owned private businesses.

[34]This has a similar impact to excluding households with less than around $80,000 in financial assets, but a fixed amount of financial assets may provide ample hedging opportunity for a low income household while being economically unimportant and insufficient to hedge labor income risks for a high income household.

[35]I use real discount rates between four and nine percent motivated by the work of Huggett and Kaplan (2012).

[36]For example, the estimated response of stock allocation to a one standard-deviation increase in permanent income variance in specification [4] in Table 1.6A shrinks from a decline of 3.16 percent to a decline of 2.30 percent when households with relatively limited financial assets are returned to the sample. The response of scaled stock allocations in Table 1.6B and leverage in Table 1.7, and responses to the other labor income risks also reduce by about 30 percent.

households with few financial assets, asset allocations should be relatively arbitrary as portfolio allocation has little welfare consequence.

Table 1.5 provides summary statistics for the 2010 wave of the SCF sample both before and after removing the excluded households. Patterns are broadly similar for the 2004 and 2007 waves. The households that remain after exclusions have median financial assets varying from \$254,000 in 2004 to \$296,000 in 2007. Of these households, between 86.0% (in 2010) and 88.5% (in 2004 and 2007) own stocks in some form. The remaining households represent about 40% of the population of workers between the ages of 25 and 60, and about 54% of the population of workers between age 40 and 60. Excluded households are disproportionately younger, less educated, and lower income. The excluded households have median financial assets varying from \$6,000 in 2010 to \$8,000 in 2007, with only about half owning stocks in some form, typically in retirement accounts.

Figure 1.3 compares the average labor income risks and stock allocations across groups of households sorted by industry, occupation, and unionization and self-employment status.[37] The size of the plotted bubbles reflect the fraction of the population represented by each group.

In Figure 1.3, the relationship between each of the four labor income risks and stock allocations is *positive*. The weighted least squares line in plot (a) shows that the relationship between the variance of permanent log labor income and stock allocations is particularly strong, with a t-statistic over 3. For example, workers in business service industries have education-adjusted stock allocations about 5% higher than average despite facing permanent labor income variance about 40% higher than average, above-average probability of job loss, and above-average permanent income cyclicality.

One concern is whether these results are driven by holdings of financial assets over which workers have little control given their employment, such as defined benefit pensions. If financial assets over which workers have no control are excluded from the computation of

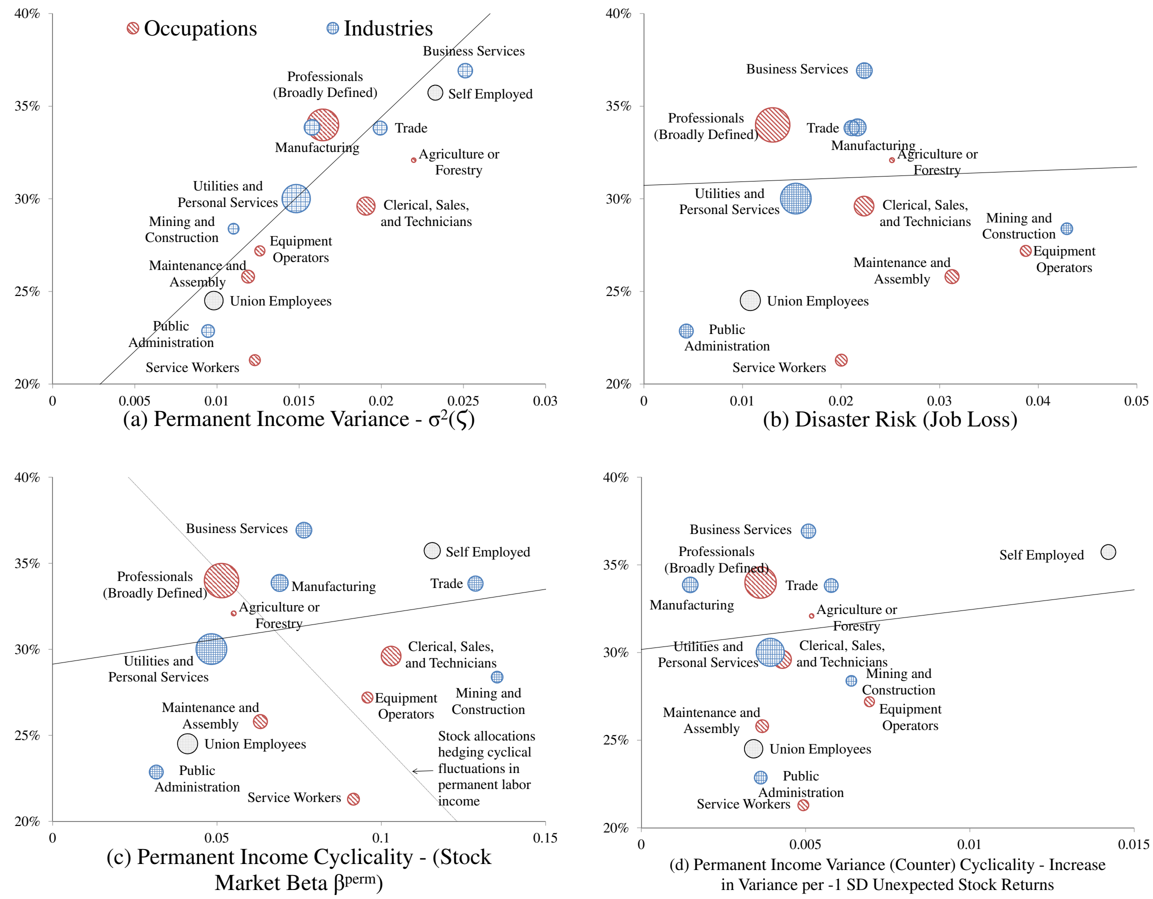
[37] Where only one of two workers in a household belongs to a group, that household's contribution towards the group's average labor income risk and stock allocation is weighted by the share of household human wealth represented by the worker belonging to the group. Group averages also account for SCF sampling weights.

Table 1.5: *Summary Statistics: Working Heads in the SCF (2010 Wave)*

SCF sampling weights are used to produce statistics in this table, and monetary amounts are given in CPI adjusted 2009 dollars. The demographic composition of workers in the 2004 and 2007 waves of the SCF are similar, though wealth levels and the value of stock holdings in particular are lowest in 2010 and highest in 2007.

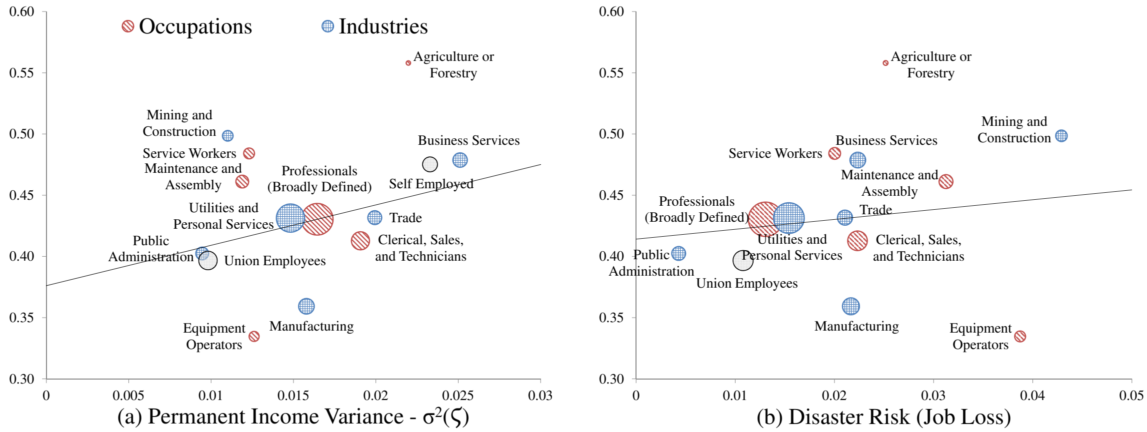
	Full Sample with Working Head				Financial Assets>Human Wealth/10 and No High-School Dropouts			
Number of Households	3,248				1,298			
		Percentiles				Percentiles		
	Mean	10th	50th	90th	Mean	10th	50th	90th
Age	42.8	29.0	43.0	56.0	48.9	38.0	50.0	58.0
Expected Future Years of Employment	23.4	7.0	22.0	41.0	15.5	5.0	14.0	28.0
Head is Male	49.4%				55.6%			
White	66.1%				78.6%			
High School Dropout	7.9%				0.0%			
High School Graduate	53.7%				46.1%			
BA Degree or Above	38.4%				53.9%			
Married	55.8%				66.9%			
Has Dependent Child	58.1%				52.8%			
Head Labor Income (000s)	$70.8	$16.8	$45.0	$120.0	$105.8	$22.0	$65.0	$190.0
Head plus Spouse Labor Income (000s)	$91.1	$20.8	$61.0	$160.0	$134.9	$29.6	$90.0	$250.0
Job Tenure (Years)	9.2	1.0	6.0	22.0	13.7	1.0	12.0	29.0
Total Financial Assets (000s)	$240.5	$0.2	$32.5	$536.6	$636.3	$59.0	$285.2	$1,429.5
Stock Share of Financial Assets	18.4%	0.0%	11.5%	67.6%	27.1%	0.0%	23.2%	60.1%
Total Private Business Wealth (000s)	$63.8	$0.0	$0.0	$11.9	$137.2	$0.0	$0.0	$116.1
Total Property Wealth (000s)	$273.0	$4.5	$148.3	$548.1	$504.4	$45.3	$286.7	$1,073.0
Total Debt (000s)	$143.1	$0.0	$78.0	$322.5	$214.6	$0.0	$116.3	$497.0

Figure 1.3: *Stock Share of Financial Assets and Labor Income Risks of Industry and Occupation Sorted Groups*



Equations (1.6), (1.7), and (1.8) are estimated using PSID data and then used to fit risks to households in the 2004, 2007, and 2010 SCF using $CHAR$, the set of worker demographics and employment characteristics. The households included for analysis are those where either the head or spouse works, is age 25 to 60, plans to work for at least two more years, has at least a high-school equivalent education, and household financial assets (excludes real property, private businesses, and human wealth) are at least one tenth that of estimated household human wealth (see Appendix A.4). Household risks and stock share are averaged by industry and occupation sorted groups for each wave of the SCF, and then averaged across the three SCF waves. Households weights within each group are proportional to the SCF sampling weights multiplied by the share of the household's human wealth represented by workers (head or spouse) that are part of the group. The size of the bubbles in the plots reflect the fraction of the included population falling into each group. The solid lines are least squares regression lines. The dashed line in the "permanent income cyclicality"plot indicates stock allocation levels which offset the variation in implicit stock market exposure assuming the average ratio of human to financial wealth in the represented population.

Figure 1.4: *Leverage (Household Debt/Equity) and Labor Income Risks of Industry and Occupation Sorted Groups*



Household leverage is computed as total household debt divided by household equity (financial assets plus property). Leverage is winsorized above at two, and set equal to two for a few households with negative equity. See the notes to Figure 1.3 for further reference, as construction is analogous.

stock allocation, the positive relationship between labor income risks and stock allocations only weakens by about 20%, mostly due a disproportionate increase in the stock shares of unionized workers, who are most likely to have significant defined benefit pensions.[38]

Figure 1.4 performs an analysis similar to Figure 1.3 using household leverage instead of stock allocations. I define household leverage as a debt to equity ratio. Debt includes all forms of household debt, most commonly, mortgages, student loans, auto loans, and credit card debt. Equity equals the value of household financial assets plus property. I do not compare leverage to the cyclical labor income risks, as these risks have no clear theoretical relationship with the attractiveness of leverage. Figure 1.4 shows that households with large unconditional labor income risks also take greater leverage, exacerbating differences in the magnitude of total wealth risks across households.

To build on the simple analysis in Figures 1.3 and 1.4, I turn to multivariate regressions of financial risk measures in Tables 1.6 and 1.7. Tobit is used to deal with censoring of stock allocations at zero. However, least squares regressions yield very similar results in all cases

[38] Households in the SCF are asked if they have control over the asset allocation in their employer pension plans.

as relatively few observations of zero debt or zero stock holdings exist in the sample I use.

In Panel A of Table 1.6, just as in Figure 1.3, the dependent variable is the value of stock owned as a fraction of total financial assets. In Panel B of Table 1.6, stock holdings are scaled by the sum of financial assets and human wealth, and labor income risks are scaled by the ratio of human wealth to financial assets plus human wealth.[39] This scaling is done to reflect the fact that portfolio adjustments motivated by labor income risk should take into account the relative value of financial assets and human wealth. In all specifications, the reported bootstrap standard errors account for the fact that the household labor income risks are estimated from the PSID panel data and adjust for multiple imputation used in the SCF.

Specification [1] in Panel A of Table 1.6 predicts household stock allocations using the four types of household labor income risk and year dummies (2004, 2007, and 2010). The primary differences between this analysis and Figures 1.3 and 1.4 are that (1) the regression considers variation in risks at the household level rather than the industry or occupation level, and (2) the analysis now conditions the relationships between labor income and financial risks on the level of the other labor income risks. The relationship of permanent income variance and stock allocations remains significantly positive. The relationship of disaster risk and stock allocations turns negative primarily because of change (1). Household level variation in disaster risk is strongly related to demographics, such as lower education levels, which predict reduced stock holdings.[40] Results are similar in Panel B.

In specification [2] of Table 1.6, I add controls for the composition of household wealth to account for potentially rational adjustments to stock allocations resulting from the ownership of real estate, private businesses, and other valuable property. Demographic variables and log household wealth are included to test the possibility that they are the cause of the positive relationship between labor income risk and stock allocations. The included demographic

[39]The specifications in Panel B all also include the ratio of financial assets to financial assets plus human wealth as a control.

[40]If Figures 1.3 and 1.4 were reproduced using demographic-based sorts (i.e. worker age, education, gender, race, and marital status), the relationships between labor income risks and stock allocations would be close to zero for all but the probability of becoming employed, where worker demographics associated with high probability of job loss are associated with lower stock allocations.

Table 1.6: *Tobit Regressions: Stock Allocations and Labor Income Risks*

Labor income risks are derived for households as described in Figure 1.3. The controls for household demographics include gender, education, race, age, age squared, marital status, whether there are children present, and the concentration of human wealth within the household. The controls for sources of household wealth include the value of (1) human wealth, (2) primary residence, (3) private business ownership, and (4) other property, scaled by combined human and financial wealth (and winsorized at a value of two). The instruments used for the SCF risk proxies in specification [4] are the same set of worker demographics and employment characteristics $CHAR$ used to parameterize the labor income risks, plus log household wealth, the relative share of human and financial household wealth, and year dummies (see Table 1.9). Identification is through the set of employment characteristics, as the other instruments are also included separately as controls. The instrumented variables are estimated using all SCF households. The bootstrap standard errors reported in ( ) account for the use of sampling weights, multiple imputation (used in the SCF), and generated regressors (instrumented labor income risks and risk tolerance proxies). Bold type indicates coefficients that are significant at a five percent level and italics indicate coefficients significant at a ten percent level.

[A]: Dependent Variable: Stock Share of Financial Assets X 100 (Unconditional Mean=31.49)

	[1]	[2]	[3]	[4]
Labor Income Risks (Standardized Units)				
Permanent Income Variance ($\sigma^2(\zeta)$)	**4.88**	**3.35**	2.40	-3.16
	(1.48)	*(1.73)*	*(1.73)*	*(2.53)*
Disaster Risk (Job Loss)	**-4.73**	-0.61	-0.52	0.80
	(1.30)	*(1.42)*	*(1.40)*	*(1.84)*
Permanent Income Cyclicality	1.75	2.23	2.51	2.26
	(1.38)	*(2.40)*	*(2.41)*	*(2.64)*
Perm. Inc. Variance (Counter) Cyclicality	0.41	-2.29	-2.54	-2.77
	(1.61)	*(1.96)*	*(1.85)*	*(2.01)*
SCF Risk Preference Proxies				
Unwilling to Take Financial Risks			**-11.96**	
			(2.16)	
Willing to Take Above Average Risks			**6.82**	
			(1.49)	
Willing to Take “Substantial”Risks			**7.29**	
			(3.46)	
Instr: Unwilling to Take Financial Risks				-8.65
				(53.49)
Instr: Willing to Take Above Average Risks				**159.44**
				(51.12)

Continued on next page.

Table 1.6: *(Continued) Tobit Regressions: Stock Allocations and Labor Income Risks*

[A]: Dependent Variable: Stock Share of Financial Assets X 100 (Unconditional Mean=31.49)				
	[1]	[2]	[3]	[4]
Instr: Willing to Take "Substantial"Risks				46.63
				(157.99)
Other Controls				
Year Dummies (2004, 2007, 2010)	Y	Y	Y	Y
Controls for Household Demographics	N	Y	Y	Y
Controls for Sources of Household Wealth and Log Household Wealth	N	Y	Y	Y
Observations (Households)	3,542	3,542	3,542	3,542
R-Squared (from Least Squares Regression)	0.045	0.102	0.139	0.121

Continued on Panel B.

controls cover gender, education, race, age, marital status, the presence of children, and the concentration of human wealth across the household.

Household demographics and wealth composition explain only part of the positive relationship between permanent income variance and stock allocations. A similar set of controls also fails to reverse the positive conditional relationship of permanent income variance and leverage seen in Table 1.7. In the next section, I show that heterogeneity in household risk preferences explains why households with volatile income hold more stock and take greater leverage.

1.3.2 How Risk Preferences Relate to the Distribution of Financial and Labor Income Risks

Households with greater risk tolerance require less compensation for bearing unconditional labor income risk. As a result, the most risk tolerant should tend to select employment with greater unconditional labor income risk. Table 1.4 shows that unconditional and cyclical labor income risks are correlated, so the risk tolerant should have greater cyclical labor income risks as well. The positive relationships seen earlier between labor income risks, stock allocations, and household leverage might be rational if the role of risk preferences in

Table 1.6: *(Continued) Tobit Regressions: Stock Allocations and Labor Income Risks*

Addition to notes from Panel [A]: The four labor income risks in this panel scaled by the ratio of household human wealth to combined household financial assets and human wealth, and are then standardized.

[B] Dependent Variable: Stock Share of Financial Assets Plus Human Wealth X 100 (Unconditional Mean=10.24)

	[1]	[2]	[3]	[4]
Scaled Labor Income Risks (Standardized Units)				
Permanent Income Variance ($\sigma^2(\zeta)$)	**2.05**	0.74	0.18	**-3.38**
	(0.59)	*(0.85)*	*(0.86)*	*(1.36)*
Disaster Risk (Job Loss)	**-1.40**	0.50	0.53	1.18
	(0.36)	*(0.49)*	*(0.49)*	*(0.72)*
Permanent Income Cyclicality	0.19	0.71	0.84	1.25
	(0.49)	*(0.89)*	*(0.89)*	*(1.09)*
Perm. Inc. Variance (Counter) Cyclicality	0.34	**-1.16**	**-1.25**	-1.41
	(0.52)	*(0.63)*	*(0.62)*	*(0.92)*
SCF Risk Preference Proxies				
Unwilling to Take Financial Risks			**-4.56**	
			(0.89)	
Willing to Take Above Average Risks			**2.30**	
			(0.61)	
Willing to Take "Substantial"Risks			**2.63**	
			(1.29)	
Instr: Unwilling to Take Financial Risks				-17.70
				(23.21)
Instr: Willing to Take Above Average Risks				**64.31**
				(22.79)
Instr: Willing to Take "Substantial"Risks				8.93
				(68.29)
Other Controls				
Year Dummies (2004, 2007, 2010)	Y	Y	Y	Y
Financial Assets as a Fraction of Financial Plus Human Wealth X Year Dummies	Y	Y	Y	Y
Controls for Household Demographics	N	Y	Y	Y
Controls for Sources of Household Wealth and Log Household Wealth	N	Y	Y	Y
Observations (Households)	3,542	3,542	3,542	3,542
R-Squared (from Least Squares Regression)	0.292	0.334	0.352	0.357

Table 1.7: *Tobit Regressions: Household Leverage and Labor Income Risks*

Household equity is the sum of household financial assets and property (primarily real estate). Household debt includes mortgages, short term debt (e.g. credit cards), and other consumer loans. See notes to Table 1.6A for further details on the estimation procedure. Standard errors are indicated in ( ). Bold type indicates coefficients that are significant at a five percent level and italics indicate coefficients significant at a ten percent level.

Dependent Variable: Household Leverage - Debt to Equity Ratio X 100, Winsorized at 200 (Unconditional Mean=42.28)

	[1]	[2]	[3]	[4]
Labor Income Risks (Standardized Units)				
Permanent Income Variance ($\sigma^2(\zeta)$)	3.79	2.14	1.33	**-12.67**
	(3.13)	*(2.18)*	*(2.15)*	*(4.91)*
Disaster Risk (Job Loss)	0.57	**-3.56**	**-3.36**	5.03
	(2.30)	*(1.72)*	*(1.68)*	*(3.42)*
SCF Risk Preference Proxies				
Unwilling to Take Financial Risks			**-10.21**	
			(3.08)	
Willing to Take Above Average Risks			**6.29**	
			(2.13)	
Willing to Take “Substantial”Risks			11.19	
			(6.11)	
Instr: Unwilling to Take Financial Risks				**-429.97**
				(85.98)
Instr: Willing to Take Above Average Risks				-28.61
				(112.28)
Instr: Willing to Take “Substantial”Risks				*-528.64*
				(301.14)
Other Controls				
Year Dummies (2004, 2007, 2010)	Y	Y	Y	Y
Controls for Household Demographics	N	Y	Y	Y
Controls for Sources of Household Wealth and Log Household Equity	N	Y	Y	Y
Observations (Households)	3,542	3,542	3,542	3,542
R-Squared (from Least Squares Regression)	0.016	0.428	0.437	0.494

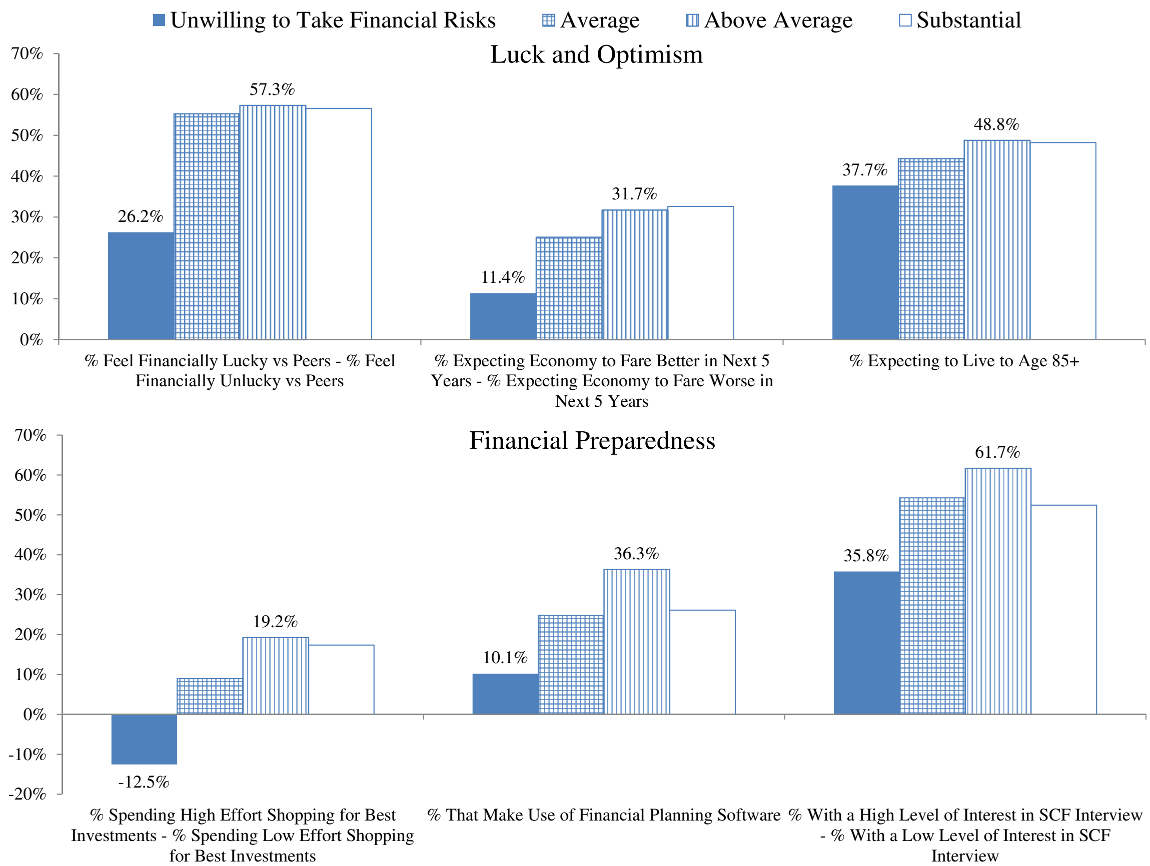
the selection of labor income risks is strong enough.

In the SCF, attitudes towards financial risk are revealed by the question, "Which...comes closest to the amount of financial risk that [your household is] willing to take when you save or make investments?"Interviewees are allowed responses of the form, "Take XXX risks, expecting XXX returns"and "Not willing to take any financial risks,"where XXX is either "substantial,""above average,"or "average."This is a coarse, self-reported measure, with responses that can be interpreted somewhat subjectively, but it still proves quite useful in explaining how risks are distributed across households. The 1996 wave of the PSID also includes a question about risk preferences. In Appendix A.5, I discuss the similarity of the SCF and PSID measures and the practical reasons why I proceed using the SCF risk tolerance proxy. The SCF measure is available for larger cross-section of households, which allows for significantly improved precision of estimates.

Self-reported willingness to take financial risk may reflect more than just the household's innate risk tolerance. First, responses may be affected by household labor income risks. If so, they partially reflect effective risk tolerance; the household's willingness to take *additional* risk. The distinction between effective and innate risk tolerance is important because the difference between the two serves as the channel by which unconditional labor income risks should cause households to reduce their financial risks. Rather than taking a stand on the extent to which the self-reported measure is a proxy for innate or effective risk preferences, I proceed with a more general interpretation. I point out where distinction between the two is important to interpretation of results.

Self-reported preferences over financial risks also appear to reflect the household's experience, outlook, and familiarity with financial risk. The top plots of Figure 1.5 show that households indicate greater willingness to accept financial risk when they feel that they have been financially fortunate and have more optimistic forecasts about economic growth and their own longevity. Similarly, Malmendier and Nagel (2011) show that willingness to accept financial risk is related to the stock market returns investors have lived through. The lower plots of Figure 1.5 suggest that households that have greater interest in financial matters are more willing to accept financial risk, though the causality in the relationship is unclear. Interest in and greater understanding of financial matters may reduce the unknowns (Knightian uncertainty) or distrust of financial markets that discourage households from taking financial risks. Alternatively, there may be greater return to paying attention to a range of investment options if you have greater innate willingness to accept financial risks.

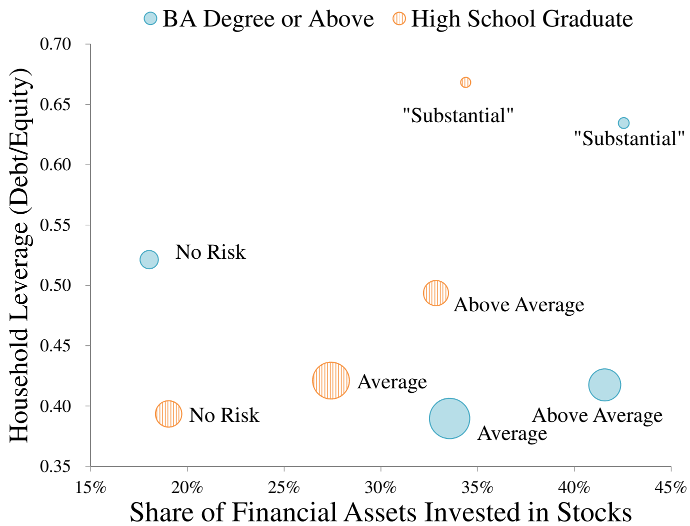
Figure 1.5: *Relationship of Self-Reported Risk Preferences with Luck, Optimism, and Financial Preparedness*



Responses above are the average across SCF waves (2004, 2007, and 2010), where the average for each wave is constructed using sampling weights.

Figure 1.6 confirms that self-reported preferences for financial risk do correspond to the financial risks which households actually take. The high leverage (debt-to-equity) of the most risk averse college educated group is largely explained by the relatively limited

Figure 1.6: *Share of Financial Assets in Stocks and Leverage by Education and Self-Reported Risk Preferences*



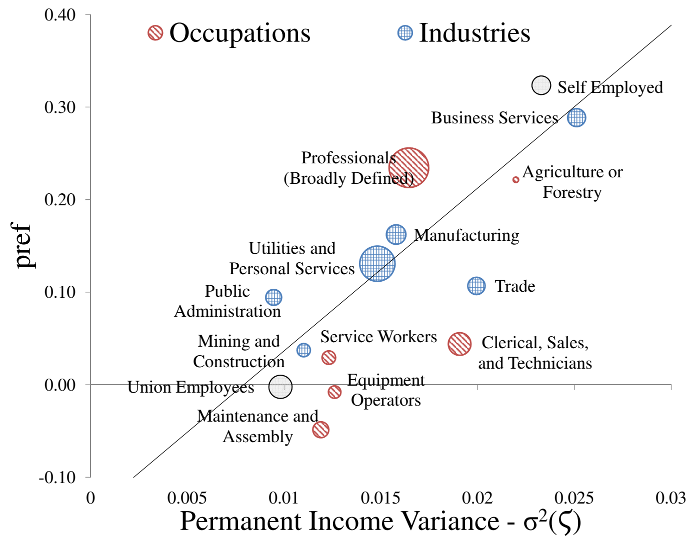
The categories plotted respond to education levels and responses to the SCF question, "Which...comes closest to the amount of financial risk that [your household is] willing to take when you save or make investments?"The population and computation of group averages is analogous to that in Figures 1.3 and 1.4. The size of the bubbles in the plots reflect the fraction of the included population falling into each group.

household equity of representatives of this group.[41] Barsky et al (1997) shows that a self-reported measure of risk tolerance found in the Health and Retirement Study and PSID also behaves as a proxy for preferences over risks to human health as well; with risk tolerant individuals reporting higher rates of smoking, drinking, and lower levels of health and life insurance. The SCF has less data on non-financial risk taking behavior, but individuals in the SCF reporting greater willingness to accept financial risk are more likely to own motorcycles relative to cars, and are more likely to respond that the reason they do not have health insurance is that they do not need it or believe in it.

Risk preferences are a source of endogeneity bias in the regressions of financial risks on labor income risks only if the risk preferences also have a role to play in the selection of labor income risks. To see if this is likely, I first define a variable called "pref"that equals one if the SCF household indicated willingness to take "above average"or "substantial"financial risks, negative one if the household indicated it was "unwilling"to take financial risks, and

[41]Household equity is a strong predictor of the debt-equity ratio as relatively low equity households must necessarily take considerable leverage to buy homes.

Figure 1.7: *Self-Reported Risk Preference and Permanent Income Variance of Industry and Occupation Sorted Groups*



The plot above represents the average household permanent income variance and "pref"for households sorted into industry and occupation groups. The risk preference measure "pref"equals 1 if the SCF household indicated willingness to take "above average"or "substantial"financial risks, -1 if the household indicated it was "unwilling"to take financial risks, and 0 otherwise. See the notes to Figure 1.3 for further details, as construction is analogous.

zero if the household was willing to accept "average"financial risks. Figure 1.7 plots the average value of "pref"against the average permanent income variance of each industry and occupation group seen in the earlier plots. The strong positive relationship in the plot suggests risk preferences are an important determinant of labor income risk.

As an extension of this simple analysis, Panel A of Table 1.8 runs regressions of standardized labor income risks on the variable "pref"and year dummies. Consistent with Figure 1.7, risk tolerant workers have higher permanent income variance. Cyclical risks are also higher for risk tolerant workers. However, disaster risk, the probability of becoming unemployed, is greater for workers reporting less willingness to accept financial risk. The concentration of disaster risk in the least risk tolerant may seem odd, but disaster risk may be largely coincidental and unavoidable.[42]

[42]Alternatively, the distribution of disaster risk could be rationalized if it has a very large negative effect on the risk tolerance that households report. This alternative is less plausible given the strong positive relationship between permanent income variance and "pref."

Table 1.8: *Least Squares Regressions: The Relationship of Self-Reported Risk Tolerance to Components of Labor Income Risk*

The risk tolerance proxy ("pref") used in these regressions equals 1 if the SCF household indicated willingness to take "above average"or "substantial"financial risks, -1 if the household indicated it was "unwilling"to take financial risks, and 0 otherwise. The dependent variables in Panel A are decomposed into components fit separately to the sets of instruments from $CHAR$ reflecting (1) quasi-exogenous worker demographics other than job tenure (education, age, gender, race, marital status, children), (2) endogenous employment characteristics (industry, occupation, self-employment, unionization), and (3) job tenure. Components (1) and (2) are used as the dependent variables in Panels B1 and B2 respectively. The risks used in this analysis pertain only to the household head (if in the labor force) to simplify the decomposition. The bootstrap standard errors reported in ( ) adjust for multiple imputation used in the SCF and generated regressors (the labor income risks). Bold type indicates coefficients that are significant at a five percent level and italics indicate coefficients significant at a ten percent level.

Number of Household Head Observations Used: 3,448

Labor Income Risk:	Perm. Income Variance	Disaster Risk (Job Loss)	Perm. Income Cyclicality	Variance Counter-Cyclicality
	[1]	[2]	[3]	[4]
[A] Dep. Variable: Standardized Household Head Labor Income Risk				
Risk Tolerance Proxy	**0.225**	**-0.133**	*0.175*	0.043
"pref"	*(0.041)*	*(0.042)*	*(0.091)*	*(0.084)*
Year Dummies	Y	Y	Y	Y
R-squared	0.028	0.008	0.016	0.003
[B1] Dep. Variable: Standardized Head Labor Income Risk Fit to Worker Demographics				
Risk Tolerance Proxy	0.022	**-0.124**	*0.164*	0.071
"pref"	*(0.039)*	*(0.035)*	*(0.091)*	*(0.055)*
Year Dummies	Y	Y	Y	Y
R-squared	0.005	0.021	0.032	0.006

Continued on next page.

Table 1.8: *(Continued) Least Squares Regressions: The Relationship of Self-Reported Risk Tolerance to Components of Labor Income Risk*

Labor Income Risk:	Perm. Income Variance [1]	Disaster Risk (Job Loss) [2]	Perm. Income Cyclicality [3]	Variance Counter-Cyclicality [4]
[B2] Dep. Variable: Standardized Head Labor Income Risk Fit to Employment Characteristics				
Risk Tolerance Proxy	**0.143**	-0.058	-0.014	-0.017
"pref"	*(0.036)*	*(0.030)*	*(0.044)*	*(0.075)*
Year Dummies	Y	Y	Y	Y
R-squared	0.031	0.005	0.001	0.004
[C] Dep. Variable: The Set of Fit Risks in [B2] Orthogonalized w.r.t. Each Other				
Risk Tolerance Proxy	**0.128**	0.020	-0.024	-0.038
"pref"	*(0.043)*	*(0.037)*	*(0.037)*	*(0.045)*
Year Dummies	Y	Y	Y	Y
R-squared	0.036	0.001	0.002	0.005

Is the relationship of labor income risks to risk preferences coincidental (and unfortunate in the case of disaster risk) or does it result from employment decisions over which the worker has control? To investigate, I decompose labor income risks into separate components attributed to worker demographics and employment characteristics. Demographics are largely outside the worker's control, while the worker's risk preferences likely play a more active role in the choice of employment characteristics. The worker demographic components of the labor income risks are constructed by fitting the instrumentation of labor income risks to only the demographic related components of $CHAR$; worker age, education, race, gender, marital status, and whether there are children in the household. Similarly, the components attributed to employment characteristics are constructed by fitting only the worker's industry of employment, occupation, self-employment, and unionization. For comparability, these components are scaled by the same standard deviation as is used to scale the labor income risks in Panel A. The worker demographics and employment characteristic components form a mostly complete decomposition of the labor income risks. Job tenure seems conceptually less endogenous than the other employment characteristics, so I leave it out of this analysis.

In Panels B1 and B2 of Table 1.8, I separately regress the demographic and employment related components of labor income risks on "pref."The regression in column [1] of Panel B2 shows that the permanent income variance associated with workers' choice of employment characteristics, industry, occupation, self-employment, and unionization, is significantly positively related to the workers' self-reported risk tolerance. Panel B1 shows that worker demographics explain little of the positive relationship of permanent income variance and "pref."

In contrast, the coefficients in specifications [2] through [4] are much more significant in Panel B1 than B2. Demographics are the primary explanation for why workers with high disaster risk report lower risk tolerance and workers with greater cyclical labor income risks report higher risk tolerance. Certain household demographics, such as less education and minority status, are associated with both higher probability of job loss and lower levels of self-reported risk tolerance.

In Panel C, the employment related components of labor income risks from B2 are orthogonalized with respect to each other. This is done to confirm that omitted variable bias due to considering the risks one at a time is not distorting the implications drawn from Panel B2. Panel C suggests that permanent income variance is the only of the four labor income risks which is considered in workers' selection of occupation, industry, and whether to self-employ or opt for union employment.

So far, the discussion of Table 1.8 has treated "pref"as a measure of innate preferences. If self-reported preferences partly reflect effective risk tolerance, the evidence that high levels of permanent labor income variance is self-selected by the risk tolerant is even stronger. For example, workers with high permanent labor income variance may have reported even greater willingness to accept financial risk if it were not for their volatile incomes.

The analysis so far demonstrates that risk tolerant households simultaneously take greater financial risk and accept employment with characteristics associated with higher permanent income variance. This makes the positive *unconditional* relationship between household labor income risks and financial risks less surprising. To investigate the relationship conditional on risk preferences, Specification [3] in Tables 1.6 and 1.7 introduces dummies for the self-reported risk preference responses. As a result, the "puzzling"evidence suggesting households increase financial risk in response to greater permanent income variance weakens, but the impact is not very large.

Error in the measurement of risk tolerance is responsible for the modest impact of adding SCF risk preference dummies. The respondent's concept of risks when "savi[ing] and investing"may vary, the four possible responses have partly subjective interpretations (e.g. what is an "average"level of risk), and the response given may be colored by the way the question is asked or the respondent's frame of mind. This measurement error, the difference between the respondent's true and self-reported risk preferences, is almost certainly correlated with household labor income risks. For example, a household that has high permanent income variance but reports only "average"willingness to accept financial risks is probably truly more risk tolerant than average. Therefore, the regression coefficients on the four labor income risks are biased when the measurement error is ignored.

To address measurement error, I use a set of instrumental variables for self-reported risk preferences.[43] The instruments include worker demographics and employment characteristics found in $CHAR$, log household wealth, the relative share of human and financial household wealth, and year dummies.

The "stage-one"regression for this instrumentation is given by Equation (1.9) and the regression coefficients, λ, are given in Table 1.9.[44] The sizable F-statistics suggest the instruments are highly relevant in predicting self-reported effective risk tolerance.

$$\begin{aligned}\text{Dummy[Willing to accept...risks]}_{i,t} =& \lambda_0 \underbrace{[1 \text{ Demographics}_{i,t} \text{ Employment Characteristics}_{i,t}]}_{CHAR_{i,t}} \\ &+ \lambda_1 \text{Total Wealth and Wealth Shares}_{i,t} + \lambda_t \end{aligned} \tag{1.9}$$

I include household demographics, wealth and wealth composition, year dummies, and the instrumented labor income risks as control variables along with the instrumented risk preferences. Household demographics are included in the set of control variables as demographics may predict financial risks even conditional on labor income risks and risk preferences.[45] Therefore, validity of the instrumentation in Equation (1.9) requires that employment characteristics (industry, occupation, self-employment and unionization) affect financial risks only through risk preferences and the set of control variables. If this is not true, the specification has further omitted variable bias. Of course, omitted variable bias may also exist even if the instruments for risk preferences are valid.

[43] Kimball et al (2008) show how, with some assumptions, repeated responses can be used to account for measurement error in self-reported risk preferences. However, the SCF (and PSID) have only one observed response to the risk preference question per household.

[44] I use all 8,315 SCF households (i.e. including those not meeting the wealth or age criteria) to estimate the instrumented risk preferences. The instrumented variables and resulting coefficient estimates are similar to those produced using only the wealthier, age-restricted subsample focused on elsewhere, but including all observations strengthens the instruments, improving statistical power.

[45] For example, more educated households may buy more stocks due to greater familiarity with financial markets or greater awareness of the equity premium.

Table 1.9: *Least Squares Regressions: Instrumentation of Self-Reported Risk Preference Responses in the SCF*

"Willing to Take Average Financial Risks"is the fourth (excluded) possible response to the survey question. Total wealth includes financial assets, human wealth, private business ownership, and property minus total household debt. The bootstrap standard errors reported in ( ) account for the use of sampling weights and multiple imputation. Bold type indicates coefficients that are significant at a five percent level and italics indicate coefficients significant at a ten percent level.

Dependent Variables (Dummies):	Unwilling to Take Financial Risk	Willing to Take "Above Average" Financial Risks	Willing to Take "Substantial" Financial Risks
Unconditional Means:	0.335	0.206	0.040
Demographics:			
High School Dropout	**0.322**	**-0.156**	-0.015
	(0.027)	*(0.019)*	*(0.010)*
High School Graduate, No BA Degree	**0.114**	**-0.095**	0.000
	(0.015)	*(0.014)*	*(0.007)*
Worker Age / 10	-0.083	**0.160**	-0.022
	(0.057)	*(0.047)*	*(0.025)*
Worker Age Squared / 100	**0.014**	**-0.022**	0.001
	(0.007)	*(0.006)*	*(0.003)*
Race is White	**-0.101**	**0.037**	-0.001
	(0.013)	*(0.011)*	*(0.006)*
Male	**-0.076**	**0.070**	**0.019**
	(0.015)	*(0.013)*	*(0.007)*
Married Couple	0.002	**-0.026**	-0.004
	(0.013)	*(0.012)*	*(0.006)*
Dependent Children in Household	*0.025*	-0.013	-0.004
	(0.013)	*(0.011)*	*(0.006)*
Employment Characteristics:			
Self-Employed	**-0.086**	**0.037**	**0.031**
	(0.017)	*(0.017)*	*(0.009)*
Unionized	0.003	*-0.029*	0.010
	(0.019)	*(0.018)*	*(0.008)*
Industry: Utilities and Personal Services - Omitted Dummy			
Mining and Construction	0.045	-0.013	0.010
	(0.029)	*(0.022)*	*(0.011)*
Manufacturing	-0.029	*0.033*	0.007
	(0.020)	*(0.019)*	*(0.009)*

Continued on next page.

Table 1.9: *(Continued) Least Squares Regressions: Instrumentation of Self-Reported Risk Preference Responses in the SCF*

Dependent Variables (Dummies):	Unwilling to Take Financial Risk	Willing to Take "Above Average" Financial Risks	Willing to Take "Substantial" Financial Risks
Trade	-0.010	0.024	0.008
	(0.020)	*(0.018)*	*(0.009)*
Business Services	**-0.046**	**0.073**	0.009
	(0.020)	*(0.022)*	*(0.010)*
Public Administration	-0.040	-0.021	0.007
	(0.026)	*(0.024)*	*(0.012)*
Occupation: Professionals - Omitted Dummy			
Clerical, Sales, and Technicians	*0.032*	-0.027	-0.001
	(0.019)	*(0.017)*	*(0.009)*
Service Workers	**0.089**	-0.018	-0.014
	(0.025)	*(0.021)*	*(0.010)*
Maintenance and Assembly	**0.055**	**-0.043**	-0.006
	(0.025)	*(0.022)*	*(0.010)*
Equipment Operators	**0.050**	*-0.035*	-0.015
	(0.025)	*(0.021)*	*(0.010)*
Agriculture, Forestry, and Animal Trades	**0.123**	-0.017	-0.013
	(0.042)	*(0.034)*	*(0.016)*
Other Controls			
Employment Tenure / 10	**0.019**	-0.006	*-0.006*
	(0.009)	*(0.008)*	*(0.003)*
Fin. Wealth/(Fin.+Human Wealth)	**-0.310**	**0.154**	0.008
	(0.032)	*(0.032)*	*(0.015)*
Log Total Wealth	**-0.077**	**0.033**	0.001
	(0.006)	*(0.006)*	*(0.003)*
Year Dummies (2004, 2007, 2010)	Y	Y	Y
Observations (Households)	8,320	8,320	8,320
R-Squared	0.476	0.263	0.049
F-value	196.7	67.6	11.1

To test the likely significance of remaining omitted variable bias, I run an analysis in Appendix A.6 motivated by the work of Altonji, Elder, and Taber (2005). This analysis uses the endogeneity of financial and labor income risks with respect to observed demographics as an estimate of the endogeneity of these risks with respect to unobserved demographic variation. Since the endogeneity of risks with respect to a wide selection of observed household demographics is quite limited, I argue that unobserved variation in household demographics is unlikely to significantly impact the results that I discuss below.[46]

Specification [4] in Tables 1.6 and 1.7 adds the instrumented risk preferences to stock allocation and household leverage regressions.

The predicted change in stock allocation resulting from a one-standard deviation increase in the unconditional variance of permanent labor income moves from *positive* 3.35% to *negative* 3.16% once risk preferences are accounted for. The corresponding predicted change in stock holdings as a percent of total financial assets plus human wealth (Panel B of Table 1.6) moves from *positive* 2.05% to *negative* 3.38%. These regressions imply that the typical household in the sample would invest between \$20,000 and \$80,000 more in stocks if they were at the 10th percentile of household permanent income variance instead of the 90th percentile of household permanent income variance. The magnitudes of these portfolio shifts are consistent with middle-aged power utility investors that have constant relative risk aversion of roughly $\gamma = 8$ (in Panel A) and $\gamma = 2$ (in Panel B) respectively (Viceira 2001).[47]

The estimated impact of a one standard deviation increase in unconditional labor income variance on household leverage moves from positive 0.02 to negative 0.13 when risk preferences are accounted for. Based on the median household equity (assets minus

[46]Specifically, unobserved demographics need to be about ten times as important as the observed demographics in explaining stock allocations and leverage in order to neutralize the negative responses to permanent income variance that I find. An informal way of showing that unobserved variation is likely to have limited impact is to note that when I include 34 more household characteristics in the SCF as additional controls, the coefficients on labor income risks change very little despite significant gains in R-squared.

[47]Viceira (2001) shows that risk tolerant households' stock allocations should be more sensitive to permanent income variance. For example, a highly risk averse household holds little stock regardless of the level of permanent income variance (except in the unlikely event that stock returns hedge the household's background risk). The declining sensitivity of stock allocations to permanent labor income variance (as risk aversion rises) is an additional testable hypothesis, but the cross-section I work with is not large enough to test this conclusively.

debt) in the sample, this implies a reduction in debt of nearly $50,000, or nearly 25% of the average total debt, per each standard deviation increase in unconditional permanent income variance. While this effect is economically large, a comparison with optimal household behavior needs to take into account the risk characteristics of the assets (typically real estate) acquired through leverage.

The impact of permanent income variance on the financial risks households take is consistent with the finding in Table 1.8 that risk tolerant households select employment with greater permanent income variance. Households are not oblivious of their permanent labor income variance. Furthermore, these results are actually stronger to the extent that the self-reported risk preferences reflect effective risk tolerance, as opposed to innate risk tolerance.[48]

Household stock allocations and leverage are not significantly affected by disaster risk; the probability of becoming unemployed. Similarly, careers bearing a high probability of unemployment do not appear to be allocated towards risk tolerant households as high permanent income variance careers are. One possibility is that households have difficulty estimating how the probability of job loss varies across careers. Alternatively, the probability of job loss may be a weak measure of disaster risk if there is substantial predictable heterogeneity in the costliness of job loss.[49]

Table 1.6 also shows that cyclical risks do not have significant impact on stock allocations. The absence of a significant response does provide evidence that households are not hedging their cyclical labor income risks as theory predicts. For example, in Panels A and B of Table 1.6 the coefficients on permanent income cyclicality should be approximately -0.20 and -0.05 respectively in order for the reduction in stock holdings to offset the exposure of permanent labor income to stock returns. Such values are over five standard errors below the actual coefficients, which are a statistically insignificant 0.02 and 0.01. In order

[48]The understatement is probably not too large given that estimated magnitude of the response of stock allocations to permanent income variance is already roughly at a level consistent with theory. This is indirect evidence that self-reported risk preferences are probably a better measure of innate than effective risk tolerance.

[49]The measure I currently use (see Equation (1.6)) treats all job loss as equally undesirable.

to hedge cyclical labor income risks, households must recognize the statistical relationship between their labor income and stock returns and then broadly frame the set of economic risks that they face when making investing and borrowing decisions. The data suggest few households have this ability.

1.4 Conclusion

Households with employment in industries and occupations with greater unconditional and cyclical labor income risks hold more stock and have greater leverage. These relationships appear to contradict established theory on how portfolios should respond to labor income risks. This puzzle is explained by the fact that risk tolerant households select employment with greater risk, and especially employment with greater permanent income variance. Conditional on risk preferences, households decrease stock allocations and leverage in response to higher permanent income variance by about as much as theory suggests. However, I find no evidence suggesting that disaster risk, modeled by the probability of job loss, affects the financial risks that households take.

I find heterogeneity in permanent income cyclicality that should lead to substantial variation in stock allocations, yet I do not find evidence that stock allocations are affected by it. As a result, households employed in procyclical industries and occupations appear to face higher marginal costs of investing in stock than households employed in acyclical industries.

One direction to take this work is to estimate the magnitude and distribution of the costs of ignoring the cyclicality of labor income and its variance. This would provide an interesting comparison with the costs of other common household investment mistakes, such as under-diversification of risky assets, non-participation in equity markets, and extrapolation of asset returns. Several aspects of investor education may prove beneficial in reducing the costs of ignoring the relationship of labor income and stock returns: building awareness about the relationship between stock returns and labor income, ensuring diversification is understood, and encouraging investors to broadly frame their risks.

Chapter 2

Getting Better: Learning to Invest in an Emerging Stock Market[1]

2.1 Introduction

It's a little better all the time. (It can't get no worse.)

Lennon and McCartney, "Getting Better,"1967.

Equities play an important role in normative theories of household investment. Because stocks have historically offered a risk premium, households with no initial exposure to the asset class can benefit from holding at least some stocks. The optimal equity allocation depends on market conditions, the equity premium, and many details of the household's financial situation, including the household's risk aversion and other risk exposures, but typical calibrations suggest it is substantial—at least for households with sufficient wealth to justify paying the fixed cost of equity market participation (Campbell and Viceira 2002, Campbell 2006, Siegel 2007).

Direct investment in stocks is not straightforward, however, and households can lose much of the benefit of stock market participation if they engage in certain widely-studied investment behaviors. Three such investment behaviors can be costly even in a market where

[1]Co-authored with John Y. Campbell and Tarun Ramadorai

all individual stocks have the same risk and the same expected return. First, *underdiversification* increases portfolio risk without increasing return (Blume and Friend 1975, Kelly 1995, Calvet et al. 2007). Second, high *turnover* of an equity portfolio leads to high trading costs (Odean 1999, Barber and Odean 2000). Third, selling stocks that have appreciated while holding those that have depreciated—a tendency known as the *disposition effect*—increases the present value of tax obligations by accelerating the realization of capital gains and deferring the realization of offsetting losses (Shefrin and Statman 1985, Odean 1998).

In a market where expected returns differ across stocks, it is also possible for households to lose by picking *underperforming stocks*. They may do this by taking risk exposures that are negatively compensated, for example by holding growth stocks in a market with a value premium, or by adopting a short-term contrarian investment strategy (perhaps driven by the disposition effect) in a market with momentum where outperforming stocks continue to outperform for a period of time. If these style tilts do not offset other risks of the household, they are welfare reducing.[2] Alternatively, households may lose by trading with informed counterparties in a market that is not strong-form efficient, and thus rewards investors who possess private information (Grossman and Stiglitz 1980, O'Hara 2003).

Households can control suboptimal investment behaviors in several ways. They can hold mutual funds as a way to gain equity exposure without trading stocks directly. This, however, may result in trade-offs between households' tendencies to engage in these behaviors, the level of fees charged by intermediaries, and the possibility that mutual fund managers may themselves be susceptible to these behaviors. Households can also learn from observing overall patterns in the market, or from their own investment experience (Nicolosi et al. 2009, Seru et al. 2010, Malmendier and Nagel 2011, 2012). In this paper we report evidence that learning from experience is important. Importantly, however, we do not claim that such learning is rational. Instead, it may reflect reinforcement learning, in which personal

[2]This is true whether risk prices are driven by fundamentals or by investor sentiment (the preferences of unsophisticated investors for certain types of stocks). In a model with fundamental risks it may be more likely that households' non-equity risk exposures justify equity positions with low expected returns, but if this is not the case such positions still reduce household welfare just as they would in a sentiment-driven model.

experiences are overweighted relative to broader patterns of evidence in historical data.

Our study uses data from the Indian equity market. For several reasons this is an ideal laboratory for studying learning among equity investors. First, India is an emerging market whose capitalization and investor base have been growing rapidly. In such a population of relatively inexperienced investors, learning may be faster and easier to detect than in better established equity markets. Second, as discussed more fully below, mutual funds account for a relatively small value share of Indian individuals' equity exposure, so it is meaningful to measure the diversification of directly held stock portfolios. The prevalence of direct equity ownership also implies that it is more important for Indian investors to develop the skills necessary to own stocks directly than it is in a mature market with a large mutual fund share. Third, India has electronic registration of equity ownership, allowing us to track the complete ownership history of listed Indian stocks over a decade. The relatively long time dimension of our panel allows us to measure investors' performance using their realized returns, a method that is vulnerable to common shocks when applied to a short panel. Moreover, our data are monthly, and this relatively high frequency allows us to more accurately measure important determinants of performance such as momentum investing and turnover.

A limitation of our Indian data is that we have almost no information about the demographic characteristics of investors. Thus we cannot follow the strategies, common in household finance, of proxying financial sophistication using information about investors' age, education, and occupation (Calvet et al. 2007, 2009a), their IQ test scores (Grinblatt and Keloharju 2011), or survey evidence about their financial literacy (Lusardi and Mitchell 2007). Instead, we study learning by relating account age (the length of time since an account was opened) and summary statistics about past portfolio behavior and investment performance to the future behavior and performance of each account.

We have four main results. First, investment performance improves with account age. Second, older accounts have several profitable tilts in their portfolio weights, particularly towards value stocks and stocks with low turnover. However, these style tilts leave much of the outperformance of older accounts unexplained. Third, two of the three potentially harmful investment behaviors that we focus on, namely high turnover and the disposition effect, are less prevalent among older accounts. Fourth, all three investment behaviors diminish in response to painful experiences, including account underperformance, large losses in a single month, and poor returns from past trading and sales of gains. Putting these results together, investors appear to learn from stock market participation, at a rate that is influenced by their investment experiences.

2.1.1 Related Literature

The behavior of individual investors in equity markets has been of interest to financial economists studying market efficiency ever since the efficient markets hypothesis was first formulated. Shleifer (2000) succinctly summarizes the importance of this line of inquiry for the study of market efficiency, outlining that theoretical defenses of the efficient markets hypothesis rest on three pillars, the first of which is rational decision making and securities valuation by individuals, the second, the absence of correlated deviations from rationality even if some investors deviate from rational decision making, and the third, limits to arbitrage.

Understanding the behavior of individual investors is also important for the field of household finance (see Campbell 2006, for example). There has been much work on theoretically optimal investment in risky assets, and deviations from such idealized behavior by households have important implications for the evolution of the wealth distribution in the economy.

While the theoretical motivation for the study of individual investors has been clear for some time, empirical work in this area has been hampered by the difficulty of obtaining detailed data on individual investors' portfolios as well as by the large computational burden imposed by the study of such large datasets. These constraints have gradually been surmounted, and this field of study has increasingly become one of the most active areas of empirical research in financial economics.

Early work in the area (Cohn et al. 1975, Schlarbaum et al. 1978, Badrinath and Lewellen 1991) utilized relatively small samples of trader accounts from retail or discount brokerages to shed light on the stocks held by individual investors, the returns they earned, and the practice of tax-loss selling. The first set of empirical studies with a primary focus on questions related to rationality and market efficiency followed in the late 1990s, also using data sourced from discount brokerages, identifying that individual investors exhibit the disposition effect (Odean 1998), and trade excessively in the sense that their transactions costs outweigh any stock-picking ability they may possess (Odean 1999, Barber and Odean 2000). These tendencies were found to vary with the demographic characteristics and trading technologies of investors such as gender, marital status, and access to online trading (Barber and Odean 2001, 2002).

A characteristic of this early literature, and continuing to the present day, is the focus on *trading* rather than *investment* decisions of individual investors. While many questions in household finance are about the performance and risk properties of the entire risky asset portfolio of individual households, much of the literature has concentrated on performance evaluation of individual investors' purchases and sales at different post-trade horizons (see, for example, Coval et al. 2005, Barber et al. 2008, Seru et al. 2010), and on contrasting individual returns with those achieved by domestic and foreign institutional investors (Grinblatt and Keloharju 2000, Kaniel et al. 2008). A related focus has been on characterizing the trading strategies of individual investors through the lens of various behavioral biases such as the disposition effect, overconfidence, or inattention (see, for example, Barber and Odean 2008 and references above), and demonstrating the types of stocks (large, hard-to-value) in which these biases are most likely to manifest themselves (Ranguelova 2001, Kumar 2009).

This focus on trades rather than on investment arises quite naturally from the limitations of the data used to study investor behavior. In the US, discount brokerage accounts from a single service provider may not be truly representative of the entire portfolio of an individual investor, a problem made significantly worse when investors also have untracked mutual fund or 401(k) investments.[3] And some international datasets, such as the Taiwanese stock exchange data used by Barber et al. (2008), track all individual investor transactions but have little detail on holdings.

Our use of Indian data on direct equity holdings and trades helps us to partially surmount this obstacle. We have a relatively high-quality proxy for total household investment in risky assets, because equity mutual fund ownership by individual investors in India is very much smaller than direct equity ownership. As explained in the next section, we estimate that Indian households' equity mutual fund holdings are between 8% and 16% of their direct equity holdings over our sample period.

There are some other countries, such as Sweden and Finland, in which both direct equity ownership and mutual fund holdings are tracked. In principle this allows for a fuller characterization of household investment, but most previous studies using data from these countries have pursued different objectives than our focus on learning to invest. For example, Grinblatt et al. (2011) show that IQ affects stock market participation using data from the Finnish registry which provides detailed information on direct equity portfolios combined with an indicator for whether the household invested in mutual funds in the year 2000. Grinblatt et al. (2012) highlight the impacts of IQ on mutual fund choice by Finnish investors using detailed data on mutual fund choices alongside less detailed information on direct equity investment. Calvet et. al (2007, 2009) use comprehensive data on Swedish investors' total wealth to shed light on stock-market participation and portfolio rebalancing, but the annual frequency of their data makes it difficult for them to evaluate higher-frequency phenomena such as momentum investing and turnover.

Several papers, including those referenced in the previous section, share our focus on learning by individual investors, but emphasize different facets of this important issue. Feng and Seasholes (2005) use data on over 1500 individual accounts from China over the 1999 to 2000 period, and find that both experience (measured by the number of positions

[3] Calvet et al. (2007), show that mutual fund investments are an important source of diversification for Swedish investors.

taken) and sophistication (measured by variables that include the idiosyncratic variance share) attenuate the disposition effect. Our analysis differs from theirs in our use of a more comprehensive set of portfolio characteristics, including the idiosyncratic variance share, and our exploration of feedback effects on future investing behavior. Linnainmaa (2010) estimates a structural model of learning and trading by investors in Finland, focusing on high-frequency traders, who make at least one round-trip trade in a given day. He finds, intriguingly, that traders appear to experiment with high-frequency trading to better understand their levels of skill, and cease trading if they experience poor returns. Our estimated feedback effects on underdiversification suggest that households also experiment with the composition of their equity portfolios, choosing to underdiversify more aggressively if they beat the market. This finding of experimentation is also consistent with Seru et. al. (2010), who carefully study the trading behavior of Finnish investors, focusing on the disposition effect. Seru et al. find that investors stop trading ("exit") after inferring that their ability is poor, and that trading experience weakens the disposition effect.[4] Our work is distinguished from this literature by our focus on investments rather than trades; to provide an instructive example, "exit"in our setting is the relatively uncommon exit of an investor from all equity positions, whereas Seru et al. use this term to refer to a period of time during which no trading occurs.[5]

Other authors have demonstrated the impacts of learning, including reinforcement learning, in other settings, such as trend following by mutual fund managers during the technology boom (Greenwood and Nagel 2009), individual investment in IPOs (Kaustia and Knüpfer 2008, Chiang et al. 2011) and household choice of credit cards (Agarwal et al., 2006, 2008). Agarwal et al. (2008) find that households learn how best to reduce fees on their credit card bills, and estimate that knowledge depreciates by roughly 10% per month,

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[4]Related work on the positive effect of trader experimentation and trader experience on returns and bias attenuation includes Dhar and Zhu (2006), Mahani and Bernhardt (2007), and Nicolosi et al. (2009). Korniotis and Kumar (2011), in contrast, find that the adverse effects of aging dominate the positive effects of experience.

[5]While the frequency of exits is relatively low in our data, we estimate two alternative specifications to account for any potential biases caused by exits that are driven either by skill or luck.

i.e., they find evidence that households learn and subsequently forget. While our current specifications do not explore this possibility, this is an important avenue that we intend to pursue in future work.

Finally, while we explore the role of personal feedback and investment experience in households' learning about investment, we do not currently consider the important topic of how social interaction or local networks affect learning (Hong et al., 2004, Ivkovic and Weisbenner, 2005, 2007).

The organization of the remainder of the paper is as follows. Section 2.2 describes our data, defines the empirical proxies we use for investment mistakes and style tilts, and presents some summary statistics. Section 2.3 relates account age to investment performance and behaviors. Section 2.4 shows that past performance predicts account behavior, while Section 2.5 shows that the behavior of the investor base predicts the returns on Indian stocks. Section 2.6 concludes.

2.2 Data and Summary Statistics

2.2.1 Electronic stock ownership records

Our data come from India's National Securities Depository Limited (NSDL), with the approval of the Securities and Exchange Board of India (SEBI), the apex capital markets regulator in India. NSDL was established in 1996 to promote dematerialization, that is, the transition of equity ownership from physical stock certificates to electronic records of ownership. It is the older of the two depositories in India, and has a significantly larger market share (in terms of total assets tracked, roughly 80%, and in terms of the number of accounts, roughly 60%) than the other depository, namely, Central Depository Services Limited (CDSL).

While equity securities in India can be held in both dematerialized and physical form, settlement of all market trades in listed securities in dematerialized form is compulsory. To facilitate the transition from the physical holding of securities, the stock exchanges do provide an additional trading window, which gives a one time facility for small investors to sell up to 500 physical shares; however the buyer of these shares has to dematerialize such shares before selling them again, thus ensuring their eventual dematerialization. Statistics from the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE) highlight that virtually all stock transactions take place in dematerialized form.

The sensitive nature of these data mean that there are certain limitations on the demographic information provided to us. While we are able to identify monthly stock holdings and transactions records at the account level in all equity securities on the Indian markets, we have sparse demographic information on the account holders. The information we do have includes the state in which the investor is located, whether the investor is located in an urban, rural, or semi-urban part of the state, and the type of investor. We use investor type to classify accounts as beneficial owners, domestic financial institutions, domestic non-financial institutions, foreign institutions, foreign nationals, government, and individual accounts.[6] This paper studies only the last category of individual accounts.

A single investor can hold multiple accounts on NSDL; however, a requirement for account opening is that the investor provides a Permanent Account Number (PAN) with each account. The PAN is a unique identifier issued to all taxpayers by the Income Tax Department of India. NSDL provided us with a mapping from PANs to accounts, so in our empirical work, we aggregate all individual accounts associated with a single PAN. PAN aggregation reduces the total number of individual accounts in our database from about 13.7 million to 11.6 million. It is worth noting here that PAN aggregation may not always correspond to household aggregation if a household has several PAN numbers, for example, if children or spouses have separate PANs.

Table 2.1 summarizes the coverage of the NSDL dataset. The first two columns report the total number of securities (unique International Securities Identification Numbers or

[6]We classify any account which holds greater than 5% of an stock with market capitalization above 500 million Rs (approximately $10 million) as a beneficial owner account if that account is a trust or "body corporate"account, or would otherwise be classified as an individual account. This separates accounts with significant control rights from standard investment accounts. Otherwise our account classifications are many-to-one mappings based on the detailed investor types we observe.

ISIN) and the total number of Indian equities reported in each year. Securities coverage grows considerably over time from just over 12,200 in 2004 to almost 23,000 in 2012, as does the number of unique Indian equities covered. Starting at 4,510 in 2004, the number of equities reaches a peak of 7,721 in 2012. When we match these data to price, returns, and corporate finance information from various datasets, we are able to match between 95% and 98% of the market capitalization of these equities, and roughly the same fraction of the individual investor ownership share each year.

The third column shows the market capitalization of the BSE at the end of each year. The dramatic variation in the series reflects both an Indian boom in the mid-2000s, and the impact of the global financial crisis in 2008.

The fourth column of Table 2.1 shows the fraction of Indian equity market capitalization that is held in NSDL accounts. The NSDL share grows from about 50% at the beginning of our sample period to about 70% at the end. The fifth column reports the fraction of NSDL market capitalization that is held in individual accounts. The individual share starts at about 18% in 2004, but declines to just below 10% in 2012, reflecting changes in NSDL coverage of institutions, as well as an increase in institutional investment over our sample period.

The sixth column shows the mutual fund share of total equities, which accounts for a little over 3.5% of total assets in the NSDL data in 2004, growing to a maximum of 4.72% in 2006, and declining to 3.97% by 2012. While comparing the fifth and sixth columns of Table 2.1 demonstrates the magnitude of direct household equity ownership relative to mutual funds, this simple comparison would lead to an overestimate of mutual fund ownership by households. SEBI data in 2010 show that roughly 60% of mutual funds in India are held by corporations.[7] Assuming that this share has been static over our sample period, and that corporations and individuals hold roughly the same fraction of equity and bond mutual funds, this leads us to estimate that mutual fund holdings were between 8% and 16% of household direct equity holdings over the sample period. We note also

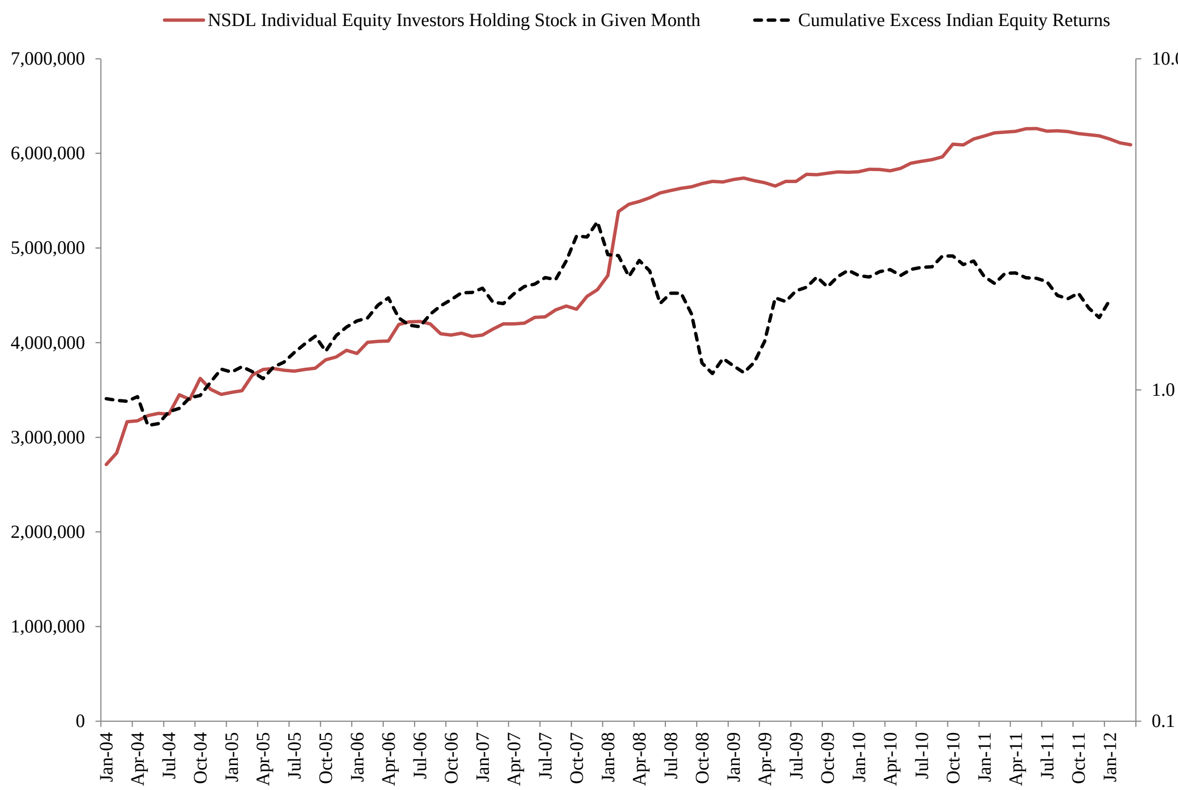
[7] See SEBI website, http://www.sebi.gov.in/mf/unithold.html.

Table 2.1: *NSDL Database Summary Statistics*

The percentages below are computed for each monthly cross-section, and the average of these monthly percentages within each year appear in the table. The number of unique securities and equities are determined by the average number of unique ISIN appearing in the NSDL database in each month in the given year. Individual accounts exclude beneficial owners. BSE market capitalization (from the World Federation of Exchanges), is from the end of each year (except 2012, where data is from October), and represents the market capitalization of all equities listed on the BSE, representing the vast majority of Indian equities.

	Unique Securities	Unique (Indian) Equities	Market Capitalization of BSE (Billions of US$)	% of Indian Equity Capitalization in NSDL Accounts	% of NSDL Equity Value in Individual Accounts	% of NSDL Equity in Mutual Funds
2004	12,264	4,510	$386.3	51.24%	17.59%	3.51%
2005	13,487	4,818	$553.1	58.04%	15.86%	3.73%
2006	15,279	5,126	$818.9	63.74%	15.04%	4.72%
2007	17,091	5,479	$1,819.1	66.72%	12.87%	4.55%
2008	17,511	5,949	$647.2	65.26%	11.94%	4.46%
2009	17,458	6,367	$1,306.5	64.73%	11.29%	4.56%
2010	19,458	6,846	$1,631.8	67.69%	10.84%	4.35%
2011	22,663	7,448	$1,007.2	69.67%	10.16%	4.00%
2012	22,696	7,721	$1,202.9	70.22%	9.90%	3.97%

Figure 2.1: *Individual Equity Investors and Cumulative Excess Indian Equity Returns*



Equity investors are defined by the aggregation of accounts by Permanent Account Number (PAN) which uniquely identify individuals. Excess Indian equity returns are computed using the yield on three-month Indian Treasury bills, and total returns and market capitalization of all Indian stocks for which we have such information.

that a 2009 SEBI survey of Indian equity-owning households found that about 65% of such households did not own any bonds or mutual funds.

Figure 2.1 illustrates the expansion of equity ownership in India by plotting the number of individual accounts active at each point in time. From the beginning to the end of our sample period, this number grew from 2.7 million to roughly 6.1 million, that is, by 125%. Equity ownership expanded throughout the decade, but the rate of growth is correlated with the return on the aggregate Indian market (illustrated by the dashed line in the figure). Growth was particularly rapid in 2004 and 2007, and much slower in the period since the onset of the global financial crisis.

2.2.2 Characteristics of individual accounts

Table 2.2 describes some basic characteristics of the individual accounts in our dataset. Because this dataset is an unbalanced panel, with accounts entering and exiting over time, we summarize it in two ways. The first set of three columns reports time-series moments of cross-sectional means. The first column is the time-series mean of the cross-sectional means, which gives equal weight to each month regardless of the number of accounts active in that month. The second and third columns are the time-series maximum and minimum of the cross-sectional mean, showing the extreme extent of time-variation in cross-sectional average account behavior.

The second set of three columns reports cross-sectional moments of time-series means calculated for each account over its active life, giving equal weight to each account which is active for at least twelve months. Since the cross-sectional dimension of the dataset is much larger than the time-series dimension, we report the 10th percentile, median, and 90th percentile of the cross-sectional distribution.

For this table and all subsequent analysis, the data used represents a stratified random sample of our full dataset, an approach we also use (and describe more fully) in the regression analysis of the next section.

Account size, number of stocks held, and location

In the first panel of Table 2.2, we begin by reporting account sizes both in rupees (using Indian conventions for comma placement), and in US dollars, both corrected for inflation to a January 2012 basis. The cross-sectional average account size varies across months from under $4,000 in 2004 to about $68,000 in June 2008, with a time-series mean of $24,760. The median account size is however much smaller at $1,330, and even the 90th percentile account size is only $10,494, reflecting positive skewness in the distribution of account sizes. This positive skewness also explains the time-series variability of cross-sectional average account size, which is strongly influenced by the entry and exit of very large accounts. The large difference between mean and median account sizes implies that the weighting scheme used in summary statistics and regressions will have an important influence on the results.

Table 2.2: *Summary Statistics for Individuals' NSDL Accounts*

Statistics are computed on the basis of all individuals' account months used in the regression models. Sampling weights are used to reflect the stratified manner in which the random sample was drawn. Time-series averages of these account-level variables are computed only for accounts which the given data appear for at least 12 months.

	Time Variation in Cross-Sectional Means			Cross-Sectional Variation in Time-Series Means		
	Mean	Min	Max	10th	50th	90th
Account Value, Jan 2012 Rs	Rs 12,62,757	Rs 2,00,160	Rs 34,66,283	Rs 7,403	Rs 67,833	Rs 5,35,213
Account Value, Jan 2012 US$	$24,760	$3,925	$67,966	$145	$1,330	$10,494
Number of Equity Positions	6.81	4.73	8.38	1.00	3.43	14.18
Urban Accounts	55.66%	54.54%	57.31%	0	1	1
Semi-Urban Accounts	12.25%	11.76%	12.77%	0	0	1
Rural Accounts	32.09%	30.39%	33.15%	0	0	1
Monthly Account Stock Return Minus Market	-0.06%	-7.77%	9.71%	-1.89%	-0.19%	1.56%
Idiosyncratic Share of Portfolio Variance	0.45	0.23	0.54	0.23	0.45	0.67
Monthly Turnover	5.59%	1.93%	12.36%	0.00%	2.26%	15.76%
Disposition Effect - ln(PGR/PLR)	1.24	-1.26	2.42	0.26	1.37	2.42
Stock Portfolio Beta	1.02	0.94	1.08	0.95	1.02	1.12
Size Percentile of Stocks Held Relative to Market Portfolio	-4.60	-6.10	-3.08	-18.24	-1.58	3.27
Book-Market Percentile of Stocks Held Relative to Market Portfolio	3.22	-5.96	17.54	-9.71	1.89	22.02
Momentum Percentile of Stocks Held Relative to Market Portfolio	-5.43	-17.18	6.05	-21.35	-5.59	4.60

Given our focus on household finance questions, as opposed to the determination of Indian asset prices, we equally weight accounts in most of our empirical analysis as advocated by Campbell (2006).

The number of stocks held in each account is also positively skewed. The average number of stocks held across all accounts and time periods is almost 7, but the median account holds only 3.4 stocks on average over its life. The 10th percentile account holds 1 stock, while the 90th percentile account holds 14.2 stocks.

The next row shows that around 56% of individual accounts are associated with urban account addresses, 32% with rural addresses, and 12% with semi-urban addresses. These relative shares do change somewhat over time.[8]

Account performance

The second panel of Table 2.2 looks at monthly account returns, calculated from beginning-of-month stock positions and monthly returns on Indian stocks.[9] These returns are those that an account will experience if it does not trade during a given month; in the language of Calvet et al. (2009a), it is a "passive return". It captures the properties of stocks held, but will not be a perfectly accurate measure of return for an account that trades within a month.

The table shows that on average, individual accounts have slightly underperformed the Indian market (proxied by a value-weighted index that we have calculated ourselves). There is considerable variation over time in the cross-sectional average, with individual accounts underperforming in their worst months by as much as 7.8% or overperforming in their best months by as much as 9.7%. This variation is consistent with the literature on institutional and individual performance in US data (e.g. Grinblatt and Titman 1993, Kovtunenko and Sosner 2004, Kaniel et al. 2008), and can be explained in part by style preferences of individual investors. There is also dramatic variation across investors in

[8]See the Appendix B.1 for a description of the method used to classify accounts into location-based categories.

[9]Appendix B.2 provides details on our procedures for calculating Indian stock returns.

their time-series average performance, with the 10th percentile account underperforming by 1.89% per month and the 90th percentile account overperforming by 1.56% per month.

Underdiversification

The next set of three rows examines account-level statistics that proxy for the investment mistakes described in the introduction. The idiosyncratic share of portfolio variance is calculated from estimates of each stock's beta and idiosyncratic risk, using a market model with the value-weighted universe of Indian stocks as the market portfolio, using a procedure very similar to that employed in Calvet et al. (2007). In order to reduce noise in estimated stock-level betas, however, we do not use past stock-level betas but instead use fitted values from a panel regression whose explanatory variables include stock-level realized betas (in monthly data over the past two years), the realized betas of stocks in the same size, value, and momentum quintiles, industry dummies, and a dummy for stocks that are less than two years from their initial listing. To reduce noise in estimated idiosyncratic risk, we estimate idiosyncratic variance from a GARCH(1,1) model.[10]

The average idiosyncratic share is 45% in both the time-series and cross-sectional moments, which is slightly lower than the median idiosyncratic share of 55% reported by Calvet et al. (2007), the difference probably resulting from our use of an Indian rather than a global market index. Once again there is considerable variation over time (from 23% to 54%) and across accounts (from 23% at the 10th percentile to 67% at the 90th percentile). However, the idiosyncratic variance share is not skewed to the same degree as the number of stocks held (reported in the top panel of the table), reflecting the convex declining relation between the number of stocks held in a portfolio and the portfolio's idiosyncratic risk.

Turnover

Turnover is estimated by averaging sales turnover (the fraction of the value of last month's holdings, at last month's prices, that was sold in the current month) and purchase turnover (the fraction of the value of this month's holdings, using this month's prices, that

[10]The GARCH model is first estimated for each stock, then is re-estimated with the GARCH coefficients constrained to equal the median such coefficient estimated across stocks. This approach deals with stocks for which the GARCH model does not converge or yields unstable out of sample estimates.

was purchased in the current month). This measure of turnover is not particularly high on average for Indian individual accounts. The time-series mean of the cross-sectional mean is 5.6% per month (or about 67% per year), and the cross-sectional median turnover is only 2.3% (or 28% per year). Turnover this low should not create large differences between the passive return we calculate for accounts and the true return that takes account of intra-month trading.

Once again, however, there is important variation over time and particularly across accounts. The 10th percentile account has no turnover at all (holding the same stocks throughout its active life), while the 90th percentile account has a turnover of 15.8% per month (190% per year).

Following Odean (1999), we have compared the returns on stocks sold by individual Indian investors to the returns on stocks bought by the same group of investors over the four months following the purchase or sale. In India, the former exceeds the latter by 2.78%, which makes it more difficult to argue that trading by individuals is not economically harmful. By comparison, the difference Odean finds in US discount brokerage data is a much smaller 1.36%. At a one year horizon following the purchase or sale, we find that stocks sold outperform stocks bought by 5.25% compared to 3.31% in Odean's data.

The disposition effect

We calculate the disposition effect using the log ratio of the proportion of gains realized (PGR) to the proportion of losses realized (PLR). This is a modification of the previous literature which often looks at the simple difference between PGR and PLR. PGR and PLR are measured within each month where the account executes a sale as follows: Gains and losses on each stock are determined relative to the cost basis of the position if the position was established after account registry with NSDL (i.e. if the cost basis is known). Otherwise, we use the median month-end price over the 12 months prior to NSDL registry as the reference point for determining gains and losses (we do this in roughly 30% of cases). Sales are counted only if a position is fully sold, although this convention makes little difference to the properties of the measure. When computing the measure, we winsorize PGR and

PLR below at 0.01.

The disposition effect is important for Indian individual accounts. On average across months, the cross-sectional mean proportion of gains realized is 1.24 log points or 245% larger than the proportion of losses realized, while the median account has a PGR that is 1.37 log points or 293% larger than its PLR. While both time-series and cross-sectional variation in the disposition effect are substantial, it is worth noting that over 90% of accounts in the sample with 12 or more months with sales exhibit this effect.

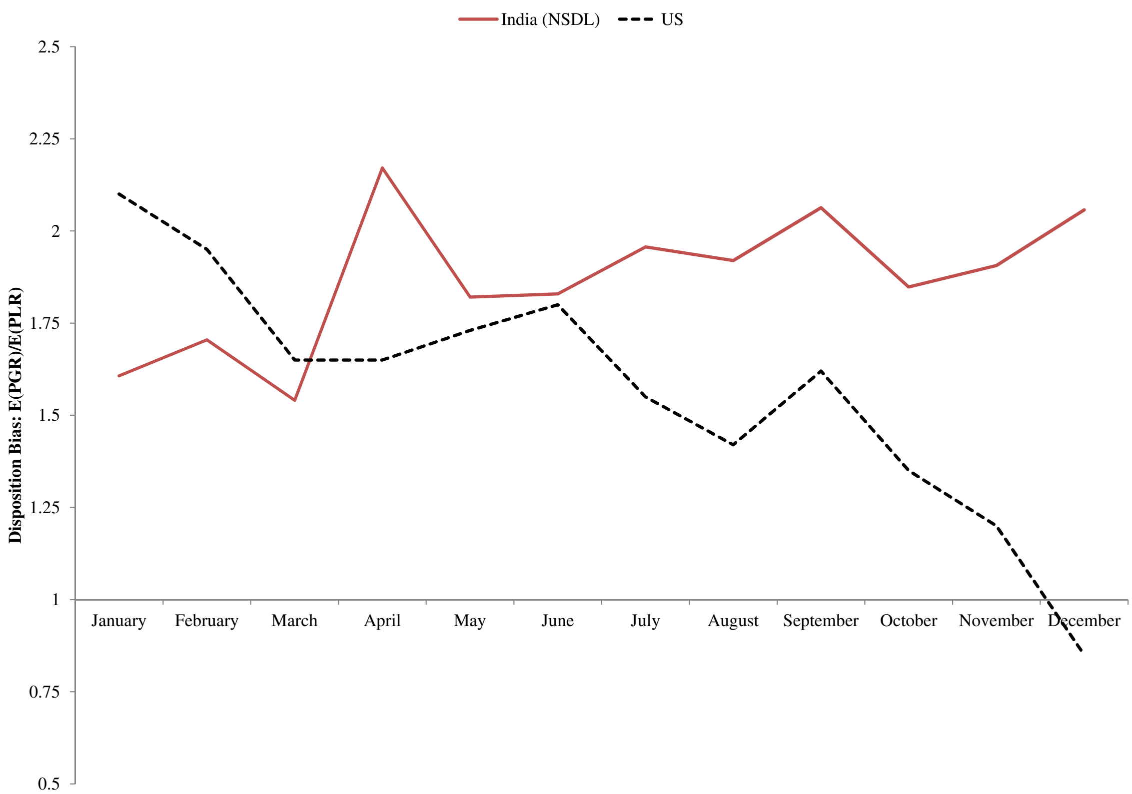
Figure 2.2 compares the disposition effect in our Indian data with US results reported by Odean (1998). The figure plots the log mean ratio of PGR to PLR by calendar month, a series that can be compared with Odean's numbers. The Indian disposition effect is considerably stronger on average than the US effect. In both India and the US, the disposition effect is weaker towards the end of the tax year (calendar Q4 in the US, and calendar Q1 in India).

Style tilts

Table 2.2 also reports several measures of individual accounts' style tilts. We construct account-level betas with the Indian market by estimating stock-level betas as described earlier, and then value-weighting them within each account. The average beta is very slightly greater than one at 1.02 in both the time-series and cross-sectional moments. The cross-sectional mean betas have modest variation over time from 0.94 to 1.08, and the cross-sectional variation in the time-series average beta is also small.

In US data, individual investors overweight small stocks, which of course implies that institutional investors overweight large stocks (Falkenstein 1996, Gompers and Metrick 2001, Kovtunenko and Sosner 2004). We measure this tendency in our Indian dataset by calculating the value-weighted average market-capitalization percentile of stocks held in individual accounts, relative to the value-weighted average market-capitalization percentile of stocks in the market index. We find a modest individual-investor tilt towards small stocks: the time-series mean percentile of market cap held by individual investors is 4.6% lower than the market index. This tilt varies modestly over time, but never switches sign. The small-cap tilt is skewed across accounts: the 10th percentile account has an 18% small-cap

Figure 2.2: *Disposition Bias of Individual NSDL Accounts vs US Discount Brokerage Accounts (Odean 98, 99)*



PGR/PLR is computed for each month, aggregating across accounts and years as in Odean (1998), which is the source for the US brokerage based statistics plotted.

tilt while the 90th percentile account has a 3% large-cap tilt.

Individual Indian investors have a very small tilt on average towards value stocks. Ranking stocks by their book-market ratio and calculating percentiles in the same manner that we did for market capitalization, we find that the time-series mean percentile of value held by individual investors is only 3.2% greater than the market index. This value tilt varies over time and does switch sign, reaching almost -6% in the month that is most tilted towards growth. There are also very large differences across accounts in their orientation towards growth or value, with a spread of over 30% between the 10th and 90th percentiles of accounts.

Finally, individual investors have a strong contrarian, or anti-momentum tilt. Ranking stocks by momentum and calculating the momentum tilt using our standard methodology, we find that both the time-series mean and cross-sectional median momentum tilts are about -5%. This pattern is consistent with results reported for US data by Cohen et al. (2002), and with short-term effects (but not longer-term effects) of past returns on institutional equity purchases estimated by Campbell et al. (2009).

Cross-sectional correlations of characteristics

Table 2.3 asks how the account characteristics described in Table 2.2 are correlated across accounts. We calculate cross-sectional correlations of account characteristics for each month, and then report the time-series mean of these correlations. To limit the influence of outliers, we winsorize account-level stock returns at the 1st and 99th percentiles, and winsorize account value below at 10,000 rupees (approximately $200).

There are a number of intriguing patterns in Table 2.3. Older accounts tend to be larger, and account age is negatively correlated with all three of our investment behavior proxies – an effect we explore in detail in the next section. Among the proxies, turnover also has a 0.34 correlation with the idiosyncratic share of variance, implying that underdiversified accounts tend to trade more. All the investment behavior proxies are positively correlated with accounts' market betas and negatively correlated with their size tilts, implying that accounts holding high-beta and small-cap stocks tend to be less diversified, trade more,

Table 2.3: *Cross-Sectional Correlations of Account Level Variables*

Statistics are computed on the basis of individuals' account months used in the regression models. Sampling weights are used to reflect the stratified manner in which the random sample was drawn. Cross-sectional correlations are computed for each month, and the average cross-sectional correlation is reported below. Account stock returns are winsorized at the 1st and 99th percentiles, and log account value is winsorized below at approximately 10,000 Rs (approximately $200).

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Account Age	[1]	1.00									
Log Account Value	[2]	**0.32**	1.00								
Account Stock Return Over the Past Year	[3]	0.03	0.08	1.00							
Idiosyncratic Share of Portfolio Variance	[4]	**-0.17**	**-0.46**	0.03	1.00						
Turnover Over the Past Year	[5]	**-0.40**	**-0.31**	0.02	**0.34**	1.00					
Disposition Effect Over the Past Year	[6]	**-0.12**	**-0.15**	0.01	0.03	0.00	1.00				
Stock Portfolio Beta	[7]	**-0.10**	**-0.14**	-0.01	**0.16**	**0.17**	0.04	1.00			
Size Percentile of Stocks Held	[8]	0.02	**0.14**	0.02	**-0.30**	**-0.13**	-0.05	**-0.33**	1.00		
Book-Market Percentile of Stocks Held	[9]	-0.01	**-0.11**	-0.09	**0.15**	0.06	0.05	**0.12**	**-0.46**	1.00	
Momentum Percentile of Stocks Held	[10]	0.05	**0.18**	**0.27**	-0.06	0.02	**-0.15**	0.00	**0.15**	**-0.26**	1.00
Urban Account	[11]	0.05	0.07	0.01	-0.03	-0.02	-0.02	-0.01	0.01	-0.01	0.02
Semi-Urban Account	[12]	0.00	-0.02	0.01	0.01	0.00	0.01	0.02	-0.02	0.02	0.00
Rural Account	[13]	-0.05	-0.06	-0.01	0.03	0.02	0.02	-0.01	0.00	0.00	-0.02

and have a stronger disposition effect. The log of account value correlates negatively with beta and value, and positively with size and momentum tilts. This implies that larger individual accounts look more like institutional accounts in that they prefer lower-beta stocks, growth stocks, large stocks, and recent strong performers. Finally, there is a strong negative correlation of -0.46 between the size tilt and the value tilt, implying that individuals who hold value stocks also tend to hold small stocks. This effect is somewhat mechanical given the correlation of these characteristics in the Indian universe.

2.3 Account Age Effects on Performance and Behavior

2.3.1 Regression specifications

In this section we explore the relation between the age of an account—our measure of overall investor experience and sophistication—and the account's performance and behavioral biases. In order to do this, we work with two alternative regression specifications. Defining an outcome (account return or behavior) for investor i at time t as Y_{it}, and the cross-sectional average of Y_{it} at time t as Y_t, we first estimate:

$$Y_{it} - Y_t = \beta(A_{it} - A_t) + s_i + \varepsilon_{it} \tag{2.1}$$

where A_{it} is a measure of the age of account i at time t, A_t is the cross-sectional average age measure for all accounts at time t, and s_i is an investor fixed effect that captures the inherent sophistication of investor i. We include the investor fixed effect to address the concern that more sophisticated investors may enter the market earlier and exit the market later than unsophisticated investors, which would make older accounts disproportionately sophisticated and would bias the estimation of a pure age effect. Equation (2.1) is our baseline specification.

A potential weakness in this approach is that the disposition effect – the tendency of investors to sell gains rather than losses – could lead to the disproportionate exit of investors who have earned high returns, presumably largely due to luck (Calvet et al. 2009a). As a consequence, older accounts may disproportionately be held by investors who had poor returns when their accounts were newer. In the presence of investor fixed effects, this biases upwards the estimated effect of account age on portfolio returns. To deal with this potential source of bias, we also estimate an alternative specification:

$$Y_{i,t} = \delta_t + \beta A_{it} + \theta C_i + \varepsilon_{it} \tag{2.2}$$

where δ_t represents an unobserved time fixed effect. The vector C_i contains measured attributes of investor i which proxy for sophistication. The C_i include initial account value, initial number of stocks held, investor location type (urban or rural), and the income and literacy levels of the Indian state in which the investor resides at the time that the account was opened. In addition we include cohort-level means of these characteristics to capture the idea that accounts opened at a time when most other accounts are sophisticated are more likely to be sophisticated themselves.

In specification (2.2), account exits driven by lucky returns have no effect on the estimated age effect, but early entry and late exit by sophisticated, skilled investors does bias upward the age effect to the extent that the variables in C_i do not fully capture investor sophistication. For these reasons, we estimate both specifications to check the robustness of our results to these two potential sources of bias. As we continue this research we plan to estimate an auxiliary model of exit in order to estimate the possible size of exit-related bias.

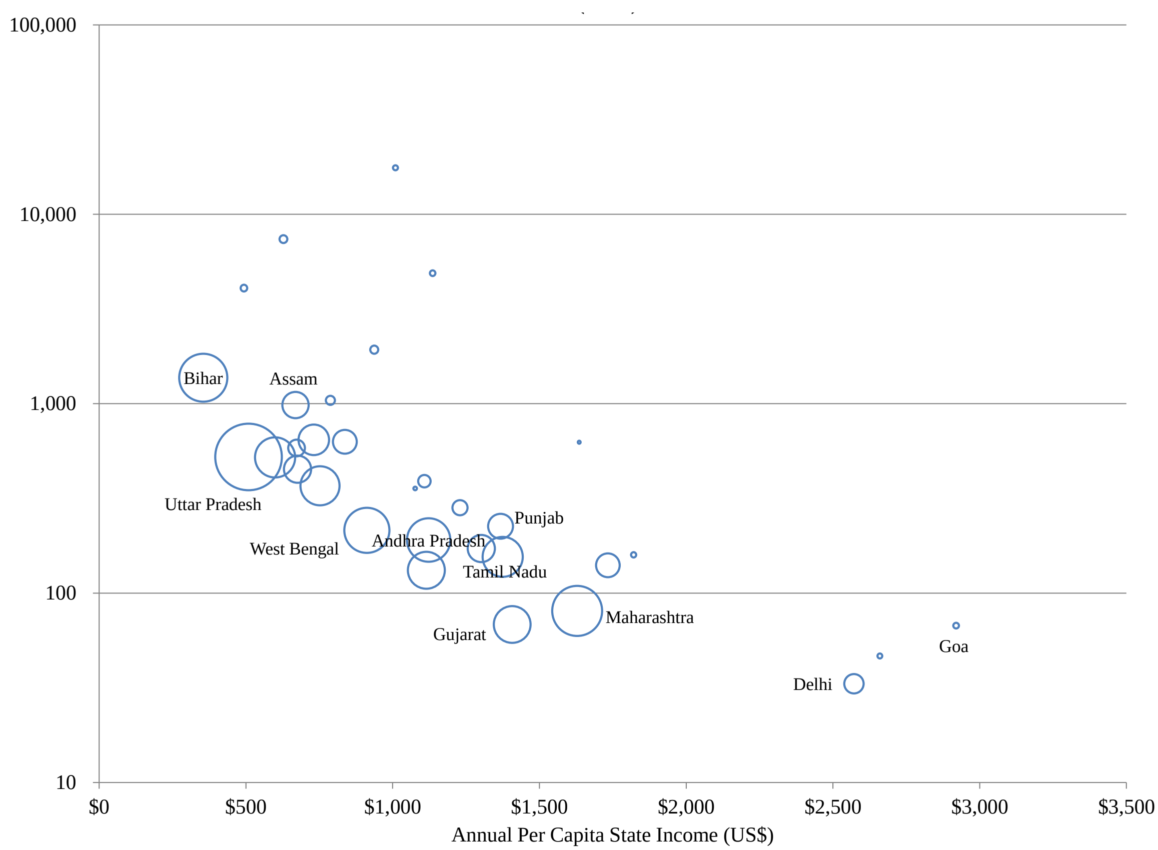
Other explanatory variables can be added to these regressions. One natural choice is account size, which we know from Table 2.3 is correlated with both account age and investment behaviors. We note however that account size is mechanically correlated with past returns. In the presence of an investor fixed effect, as in specification (2.1), this can lead to a spurious negative effect of size on returns along with a spuriously positive fixed effect for accounts that experience high early returns. Accordingly we exclude account size from our regressions predicting returns, although we have confirmed that the inclusion of size in specification (2.2) has little impact on the reported results. Investment behaviors can also be added as regressors in both specifications (2.1) and (2.2).

In both regression specifications we consider several possible forms for the account age effect. First and most simply, we consider linear age effects: $A_{it} = Age_{it}$. Since there is no particular reason why an investor's expected returns or behavior should be a linear function of account age, we also model account age effects as a piecewise linear form of account age. The curvature of the piecewise linear age effects suggests age effects of the form $A_{it} = Age_{it}^{0.5}$, which we adopt as our benchmark for the non-linear functional form of account age effects.

These regressions are estimated on a stratified random sample, drawing 5,000 individual accounts from each Indian state with more than 5,000 accounts, and all accounts from states with fewer than 5,000 accounts. Figure 2.3 shows the distribution of NSDL accounts from various states. The size of the bubbles in the plot are proportional to the population of each state. The Y-axis shows the number of people in each state per NSDL account, and the X-axis plots the per-capita income of the state in 2011. For example, in Bihar, a poor state with a per-capita annual income of roughly \$350 per annum, 1 in 1400 people invest in the stock market and are captured in NSDL data, whereas the small, relatively wealthy state of Delhi, with per-capita annual income of roughly \$2600, has 1 in 33 people participating and captured in NSDL. Given that the NSDL share of total equity capitalization is around 70% in 2012, these fractions are relatively accurate representations of total participation (without accounting for pure indirect equity ownership) by individual households in the stock market.

Our return regressions are estimated using 4 million account months of data spanning January 2004 through January 2012, and our regressions of account behaviors use somewhat fewer observations, as these measures cannot be defined for as many account months. We estimate panel regressions applying equal weight to each cross-section, and within each cross-section, we use weights to account for the sampling strategy. Standard errors are computed by bootstrapping months of data, to account for any possible contemporaneous correlation of the residuals.

Figure 2.3: *State Population per Individual NSDL Account by Per Capita State Income (2011)*



Bubble size is proportional to state population in 2011 (Indian Census). State per capita income data is as of March 2011 from the Reserve Bank of India.

2.3.2 How performance improves with age

Table 2.4 reports four variants of our basic regression approach and documents the relationship of our behavior measures to returns at the account level. The first three columns predict account returns relative to the cross-sectional average of all account returns (specification 2.1), while the next three columns (specification 2.2) allow for a time effect. The effect of age is estimated either to be linear (columns [a] and [c]) or square-root (columns [b]), where the coefficients reported give the expected performance of a one-year-old account relative to a brand new account. The linear age effect is estimated to be about 14 basis points per month in specification 2.1, and 11 basis points per month in specification 2.2, and both effects are statistically significant at the 5% level. The square-root age effect is greater for a one-year-old account (39 basis points in specification 2.1 and 30 basis points in specification 2.2), but of course it dies off more rapidly and the coefficient is only statistically significant at the 10% level for specification 2.2.

Columns [c] of Table 2.4 show that the age effect in returns barely changes once we control for lagged investor behaviors. The superior performance of older accounts cannot be purely attributed to any propensity of older accounts to better diversify, trade less, or show less disposition bias.

Figure 2.4 illustrates the choice between a linear and a square-root functional form, with results for account returns shown in the top left panel of the figure. The solid line shows the estimates from a more general piecewise linear function of age, while the dashed lines illustrate three parametric models, linear, square-root, and cube-root. The piecewise linear function is upward-sloping but somewhat jagged, and evidence for concavity is quite weak.

An important question is how more experienced investors achieve higher average returns. In Table 2.5 we attempt to answer this question by forming a zero-cost portfolio that goes long stocks held by a representative experienced investor (a stratified-sample-weighted average of the portfolio weights of accounts in the oldest quintile), and goes short stocks held by a representative novice investor (a stratified-sample-weighted average of the portfolio weights of accounts in the youngest quintile). Figure 2.5 illustrates the cumulative excess

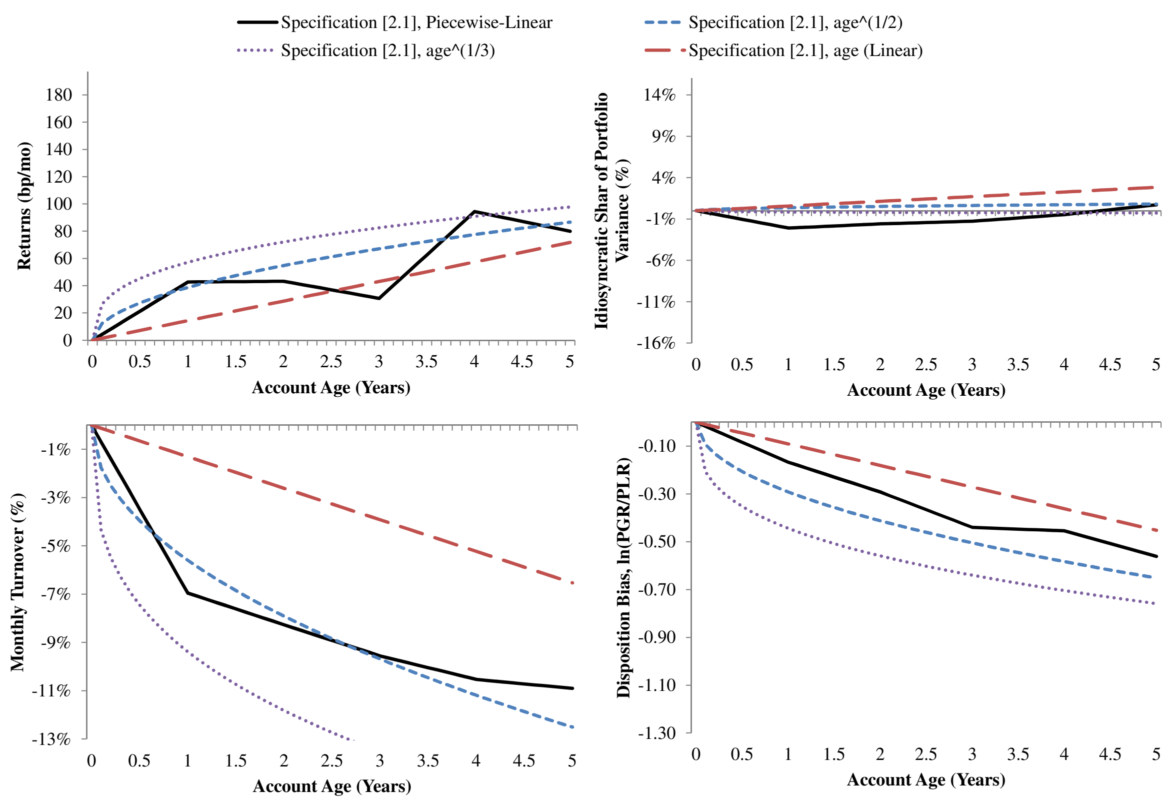
Table 2.4: *Account Age Effects in Equity Portfolio Returns*

A bit over 4 million account months from our stratified random sample spanning January 2004 through January 2012 are used in the regressions. Specification 2.1 is $(R_{it} - R_t) = \beta(A_{it} - A_t) + \kappa(B_{it} - B_t) + s_i + \varepsilon_{it}$, and specification 2.2 is $R_{it} = \delta_t + \beta A_{it} + \kappa B_{it} + \theta C_i + \varepsilon_{it}$, where R_{it} represents the returns of investor i in month t, A represents the account age (in columns [a] and [c]) or its square root (in column [b]), B are the lagged account behaviors appearing in columns [c], and δ and s are time and individual fixed effects. Lagged behaviors are averages over the past 12 months, with values winsorized at the 1st and 99th percentile of accounts for which at least five observations of the given behavior are available over the past year. Where missing, the (de-meaned) values of lagged behaviors are imputed as zeros. The account characteristics C_i include initial log account value, initial log number of equity positions, rural/urban account address dummies, and the time-series average income and recent literacy rate of the state in which the account is from, as well as the cohort level means of each of these account-level characteristics. Several variables in C_i are unavailable for pre-2002 cohorts, so these cohorts are excluded. Panel regressions are run using weights that account for sampling probability and further apply equal weight to each cross-section (month). Standard errors in ( ) are computed from bootstraps of monthly data. Coefficients that are significant at a five percent level are in bold type, and coefficients that are significant at a ten percent level are in italics. Incremental R-squared is the ratio of the variance of the fitted age effects to the variance of the dependent variable.

Dependent Variable: Account Monthly Return Minus Risk-Free Rate (bp) (Mean: 110.2bp)

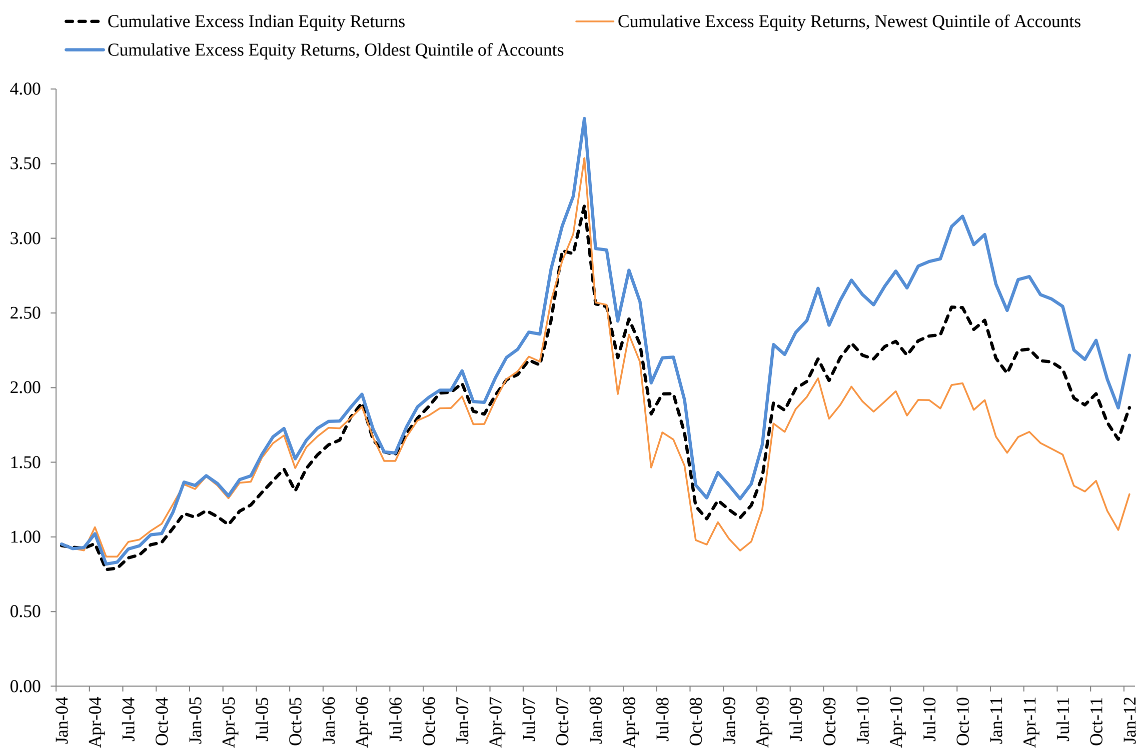
		Specification 2.1			Specification 2.2		
		[a]	[b]	[c]	[a]	[b]	[c]
	Account Age	**14.34**		*13.00*	**11.02**		**11.32**
		(7.11)		*(7.27)*	*(4.77)*		*(5.06)*
	Account Age$^{1/2}$		38.73			*29.71*	
			(24.62)			*(16.37)*	
Investor Behavior	Lagged Idio. Share of Portfolio Var.			54.73			102.02
				(82.98)			*(83.62)*
	Lagged Portfolio Turnover			**-159.34**			-110.75
				(73.69)			*(75.21)*
	Lagged Disposition Bias			-2.45			-0.45
				(2.02)			*(1.97)*
Incremental R^2		0.00040	0.00031	0.00033	0.00023	0.00018	0.00025

Figure 2.4: *Account Age Effects in Equity Portfolio Returns and Investing Behavior*



The blue and red dashed curves represent the age effects estimated in Tables 2.4 and 2.7 under Specification 2.1 (individual fixed effects). The purple dashed curve represents estimated age effects when the impact of age on the given behavior is a function of age$^{1/3}$. Similarly, the solid black line is produced by specifying age effects as a piecewise-linear function with breakpoints every year (out to five years). The vertical axis in each plot is scaled to a range equal to twice the cross-sectional standard deviation of the measured behavior.

Figure 2.5: *Cumulative Indian Excess Equity Return Received by Oldest and Newest Quintile of Accounts*



Each month, representative portfolios are formed using the average portfolio weights across accounts in the oldest and newest quintile of individual investor accounts. This plot subtracts the yield on three-month Indian Treasury bills from returns on these portfolios, as well as from the market portfolio.

returns to the long and short legs of this portfolio relative to the Indian short rate, along with the overall excess return of the Indian equity market, over the period January 2004-January 2012. By the end of this period the cumulative excess return on the experienced-investor portfolio was 122%, while the cumulative excess return on the Indian market index was 87%, and the cumulative excess return on the novice-investor portfolio was only 29%.

In the first column of Table 2.5, we regress the portfolio weights in the zero-cost portfolio onto a vector of stock characteristics, to see what characteristics are preferred or avoided by experienced investors relative to novice investors. In the second column, we decompose the returns on the zero-cost portfolio into unconditional and timing effects related to either stock characteristic tilts or a residual that we call "selectivity"following Wermers (2000). The top half of this column reports the unconditional contribution of each stock characteristic

Table 2.5: *Decomposition of the Difference in Returns on Old and New Accounts*

For the period January 2004 through January 2012, a zero-cost portfolio is formed which buys the each stock in proportion to its average weight in the oldest quintile of accounts and sells each stock in proportion to its average weight in the newest quintile of accounts. Stocks with market capitalization below 500 million Rs (approximately \$10 million) are excluded during formation of the portfolio, leaving 2,677 stocks j in the sample. Columns [1] and [3] report the time-series average of coefficients, $\bar{\phi}$, from the Fama MacBeth regression $W_{jt} = \phi_t X_{jt} + \varepsilon_{jt}$ of portfolio weights W on the set X of cross-sectionally de-meaned stock characteristics below. Normalized rank transforms are used to measure market capitalization, book-market, prior returns (momentum), turnover, and beneficial and institutional ownership shares. In columns [2] and [4], we decompose the returns in the zero-cost portfolio. Total returns ($\Sigma_j W_{jt} R_{jt}$) on the zero-cost portfolio are first broken into timing effects ($\Sigma_j W_{jt} R_{jt} - \Sigma_j \bar{W}_j \bar{R}_j$) and selection effects ($\Sigma_j \bar{W}_j \bar{R}_j$). To decompose timing and selection effects, we run Fama MacBeth regressions of returns on stock characteristics ($R_{jt} = \psi_t X_{jt} + \eta_{jt}$). Selection effects are decomposed into "stock characteristic selection"($\Sigma_j (\bar{\phi}\bar{X}_j)'(\bar{\psi}\bar{X}_j)$) and "additional stock selection"($\Sigma_j \bar{\varepsilon}_j \bar{\eta}_j$) effects. We further decompose the "stock characteristic selection"effect into components attributed to marginal returns associated with each stock characteristic c ($\Sigma_j \bar{\psi}_c \bar{x_{c,j}} (\bar{\phi}\bar{X}_j)$). Timing effects are decomposed into "stock characteristic timing"($\Sigma_j [(\phi_t X_{jt})'(\psi_t X_{jt}) - (\bar{\phi}\bar{X}_j)'(\bar{\psi}\bar{X}_j)]$) and "additional stock timing"($\Sigma_j (\varepsilon_{jt}\eta_{jt} - \bar{\varepsilon}_j \bar{\eta}_j)$), where the t-subscriped coefficients are from the cross-sectional regressions run in Fama MacBeth estimation. Standard errors given in ( ) are computed by bootstrap, with standard errors in the top half of columns [2] and [4] accounting for the uncertainty in coefficients in columns [1] and [3]. Bold type indicates coefficients that are significant at a five percent level and italics indicate coefficients significant at a ten percent level.

	1000 x Portfolio Weight (Old minus New)	Contribution to Difference in Returns (bp/mo)	1000 x Portfolio Weight (Old minus New)	Contribution to Difference in Returns (bp/mo)
	[1]	[2]	[3]	[4]
Market beta	-0.603	0.79	-0.656	0.78
	(0.420)	*(1.99)*	*(0.420)*	*(2.04)*
Market capitalization	**-0.555**	-0.14	-0.230	-2.60
	(0.274)	*(2.22)*	*(0.223)*	*(2.33)*
Book-market	**0.337**	**3.92**	**0.238**	**3.24**
	(0.100)	*(1.65)*	*(0.113)*	*(1.57)*
Momentum (t-2:t-12 returns)	0.077	**2.24**	0.046	*1.62*
	(0.170)	*(1.00)*	*(0.158)*	*(0.92)*

Continued on next page.

Table 2.5: *(Continued) Decomposition of the Difference in Returns on Old and New Accounts*

	1000 x Portfolio Weight (Old minus New)	Contribution to Difference in Returns (bp/mo)	1000 x Portfolio Weight (Old minus New)	Contribution to Difference in Returns (bp/mo)
	[1]	[2]	[3]	[4]
Stock turnover	**-0.972**	**10.29**	**-0.988**	**8.19**
	(0.186)	*(2.30)*	*(0.186)*	*(1.99)*
Beneficial ownership	**-0.673**	1.33	**-0.639**	1.17
	(0.248)	*(3.79)*	*(0.218)*	*(3.66)*
Institutional ownership	**0.769**	2.01	**0.770**	2.05
	(0.228)	*(3.45)*	*(0.226)*	*(3.47)*
Ln(1+stock age)	**0.493**	1.77	-0.114	2.24
	(0.121)	*(4.53)*	*(0.080)*	*(3.16)*
Large IPOs (market cap if age<1 year)			**-12.690**	-0.53
			(3.108)	*(1.95)*
Stock characteristic selection		**22.20**		**16.17**
		(6.78)		*(6.70)*
Additional stock selection		6.78		6.57
		(13.04)		*(14.11)*
Stock characteristic timing		-1.82		-1.80
		(11.72)		*(16.50)*
Additional stock timing		11.52		17.74
		(18.37)		*(19.72)*
Total difference in old and new account returns		38.67		38.67
		(26.94)		*(26.94)*

tilt to returns, reporting standard errors that take into account the sampling error in returns to characteristics as well as uncertainty in the characteristic tilt itself. The lower part of this column reports the overall performance contribution of all unconditional characteristic tilts, together with the contributions of unconditional stock selectivity, and stock characteristic and other stock timing effects. The third and fourth columns of the table repeat this exercise adding a variable for large, attention-grabbing initial public offerings, to capture the idea that such events might be important contributors to the performance of novice investors.

Table 2.5 shows that relative to novice investors, experienced Indian investors tilt their portfolios towards low-beta stocks; this has a minimal effect on return while reducing risk. Experienced investors also have little systematic preference for momentum. However, they do have a number of other important characteristic tilts. They favor small stocks, value stocks, stocks with low turnover, stocks without large beneficial ownership, stocks held by institutions, and older stocks. All of these tilts except for the size tilt, which contributes negligibly, are return-enhancing. In particular, more experienced investors enjoy higher returns from their tilts towards value stocks and low turnover stocks.

Taken together, the stock characteristics explain 22 basis points per month out of a total excess return of 39 basis points. The remainder is not explained by characteristic timing, which makes an insignificant negative contribution of -2 basis points. The remaining 19 basis points of performance are split between non-characteristic related stock selection (7 basis points) and stock timing effects (12 basis points). Results are generally similar when we add in a dummy for large IPOs, though the apparent preference of older accounts for older stocks appears to be entirely due to their avoidance of large IPOs.

The characteristic tilts documented in Table 5 suggest that performance evaluation of experienced investors relative to novice investors may need to correct for exposures to systematic risk factors. Table 2.6 compares raw excess returns to CAPM and multi-factor alphas for the long-short portfolio constructed in Table 2.5. The first column of the table reports a raw excess return of 39 basis points per month, which is statistically significant only at the 10% level because of noise created by market movements. The second column shows that this corresponds to a CAPM alpha of 54 basis points per month—significant at the 5% level—and a negative market beta of -0.15, reflecting the fact that older accounts tend to hold somewhat lower-beta stocks even while delivering a higher return. The third and fourth columns show that the alpha increases to 64 basis points per month in a Fama-French-Carhart four-factor model including momentum, and 93 basis points per month in a six-factor model that includes factors for short-term reversals and illiquidity (proxied by a long-short portfolio constructed by sorting the universe of stocks on turnover). Interestingly, the long-short portfolio has negative loadings on an Indian version of the Fama-French HML factor and our illiquidity factor, despite the preference of experienced investors for stocks with high book-market ratios and lower turnover documented in Table 2.5.

2.3.3 How behavior changes with age

We now ask whether our three proxies for investment behaviors change with the age of the account. Table 2.7 predicts the idiosyncratic variance share, turnover, and disposition bias measured by the log ratio of PGR to PLR, again using our two specifications (2.1) and (2.2) and allowing for either a linear or square-root age effect. While a positive linear age effect fit performance better, turnover is better captured by a negative square-root function of age. This is shown by the incremental R^2 statistics reported in the table, which measure the contribution of the age variable to the overall fit of the regression, and are markedly higher for the square-root specification. The piecewise linear regressions shown in the lower left panel of Figure 2.4 is also clearly declining and convex.

The age effects documented in Table 2.7 are not only statistically significant, but large in economic magnitude. To see this, the vertical axes on the plots in Figure 2.4 are scaled to have a range equal to twice the cross-sectional standard deviation in returns or behavior. Over the course of five years, monthly turnover declines by 11 percentage points and disposition bias declines by 56 log percentage points, both of which are on par with or greater than the cross-sectional standard deviation. In contrast, the portfolio share of idiosyncratic variance changes little with age. This may not be surprising when considering the results of Ivkovic

Table 2.6: *Performance Evaluation of the Difference in Returns on Old and Young Account Quintiles*

The zero-cost portfolio evaluated below is the difference in the representative portfolio held by the oldest quintile of accounts and the representative portfolio held by the youngest quintile of accounts (as in Table 2.5). Portfolio returns are adjusted using unconditional CAPM, four, or six factor models, where the factor returns (except Illiq) are constructed in an analogous way to the factor returns from Ken French's website. The yield on three-month Indian Treasury bills is used as the risk free rate. The illiquidity factor is constructed from an independent double sort on size and turnover over the past 12 months: Illiq=0.5 x (Small, Low Turnover-Small, High Turnover)+0.5 x (Large, Low Turnover-Large, High Turnover). All standard errors are computed using a Newey West adjustment for serial correlation (with three lags). Bold type indicates coefficients that are significant at a five percent level and italics indicate coefficients significant at a ten percent level.

	Raw Returns	CAPM	Four Factor	Six Factor
	[1]	[2]	[3]	[4]
Monthly alpha	*0.39%*	**0.54%**	**0.64%**	**0.93%**
	(0.21%)	*(0.22%)*	*(0.19%)*	*(0.27%)*
Factor Loadings				
Market beta		**-0.15**	*-0.11*	*-0.11*
		(0.04)	*(0.06)*	*(0.06)*
SMB			0.01	0.03
			(0.03)	*(0.03)*
HML			-0.08	*-0.14*
			(0.08)	*(0.08)*
UMD			0.05	0.06
			(0.05)	*(0.05)*
Short Term Reversals				*-0.12*
				(0.07)
Illiquidity				-0.09
				(0.09)

Table 2.7: *Account Age Effects in Individuals' Equity Investing Behavior*

Results are constructed from the subsample of data used in Table 2.4 where lagged equity investing behaviors are measurable. About 3.3 million account-months are used in the idiosyncratic variance share and turnover regressions, and about 400 thousand in the disposition bias regressions (disposition bias is only defined for account months in which there are both gains and losses, and trading occurs). Specification 2.1 is $(Y_{it} - Y_t) = \beta(A_{it} - A_t) + \lambda(V_{it} - V_t) + s_i + \varepsilon_{it}$, and specification 2.2 is $Y_{it} = \delta_t + \beta A_{it} + \lambda V_{it} + \theta C_i + \varepsilon_{it}$, where Y_{it} represents the indicated behavior of investor i in month t and V is log account value from the end of the previous month (winsorized below at 10,000Rs or about \$200). See Table 2.4 for definitions of other terms. Panel regressions are run using weights that account for sampling probability and further apply equal weight to each cross-section (month). Standard errors in ( ) are computed from bootstraps of monthly data. Bold type indicates coefficients that are significant at a five percent level and italics indicate coefficients significant at a ten percent level. Incremental R-squared is the ratio of the variance of the fitted age effects to the variance of the dependent variable.

	Idiosyncratic Share of Portfolio Variance (%)		Monthly Turnover (%)		Disposition Bias - ln(PGR/PLR) x 100	
Mean:	44.72%		5.06%		124.18	
Specification:	[2.1]	[2.2]	[2.1]	[2.2]	[2.1]	[2.2]
[A] Linear Age Effect						
Account Age	**0.57**	-0.08	**-1.31**	**-1.39**	**-9.33**	**-6.05**
	(0.08)	*(0.05)*	*(0.09)*	*(0.09)*	*(1.07)*	*(0.68)*
Log(Account Value)	**-5.58**	**-6.18**	**0.80**	**0.60**	-1.48	**-4.42**
	(0.09)	*(0.08)*	*(0.07)*	*(0.04)*	*(1.52)*	*(1.27)*
Incremental R^2	0.0027	0.0001	0.0250	0.0282	0.0051	0.0021
[B] Age Effect=$\sqrt{\text{Account Age}}$						
$\sqrt{\text{Account Age}}$	*0.36*	**-1.09**	**-5.59**	**-5.21**	**-29.94**	**-19.05**
	(0.22)	*(0.18)*	*(0.27)*	*(0.24)*	*(2.97)*	*(2.17)*
Log(Account Value)	**-5.40**	**-6.12**	**1.08**	**0.69**	-0.76	**-4.14**
	(0.10)	*(0.08)*	*(0.07)*	*(0.04)*	*(1.52)*	*(1.26)*
Incremental R^2	0.0001	0.0011	0.0349	0.0346	0.0056	0.0023

et al (2008), who suggest that underdiversification may also represent extreme sophistication – they find that individual trader performance improves as the number of stock holdings decrease, holding other determinants of performance constant. In addition, Table 2.5 showed that experienced Indian investors have a preference for small value stocks, which have unusually high idiosyncratic volatility.

2.4 Investment Experience and Behavior

Since behavior changes dramatically with account age, it is plausible that it may also be affected not only by the fact of investing, but also by the experiences that investors have in the market. We explore this possibility in Table 2.8, which uses fixed-effect regressions (2.1) to predict our three proxies for investment mistakes. All regressions include square-root age effects and account size controls as in the previous section.

Panel A of Table 2.8 predicts the idiosyncratic share of portfolio variance. The predictor variables are two summaries of past investment success: the cumulative outperformance of the account relative to the market, and the worst monthly return experienced by each account. Cumulative account outperformance may lead investors to assess their investing skills more optimistically, encouraging them to make larger idiosyncratic bets. Large negative returns may remind investors of the risks of stock market investing in general, and undiversified investing in particular. Both variables enter strongly, with positive and negative signs respectively. However, this result must be interpreted with some caution because the effect of cumulative outperformance may result in part from inertia. If an account has a diversified component and an undiversified bet, the weight of the undiversified bet increases with its return if the account is not rebalanced, and this will mechanically increase the idiosyncratic share of variance.

In panel B of Table 2.8 we predict turnover from the cumulative increase in returns due to trades, a measure of an account's past trading success. For each month, the return to trades is calculated as the difference between actual returns in the current month and the returns that would have been experienced if the account had stopped trading three months

Table 2.8: *Response of Individual Investor Behavior to Feedback*

The same sample is used as in Table 2.7. The regression is a variation on specification 2.1: $(Y_{it} - Y_t) = \beta(A_{it} - A_t) + \lambda(V_{it} - V_t) + \eta(F_{it} - F_t) + s_i + \varepsilon_{it}$. The s_i are account fixed effects and the terms Y, A, V, and F are cross-sectionally de-meaned account behavior, square root of account age, (winsorized) log account value, and the feedback measures used below. The increase in returns due to trades for a given month is computed as the difference between actual returns in the current month and the returns that would have obtained if no trades had been made in the past three months. The cumulative value of this measure is used below. The cumulative increase in returns due to selling off gains versus losses is computed by comparing the three-month returns following past sales with market returns over that period, with each gain and loss weighted in proportion to the value of the sale relative to the investor's stock portfolio and the outperformance of gains counting negatively in the measure. Panel regressions use weights that account for sampling probability and further apply equal weight to each cross-section (month). Standard errors in ( ) are computed from bootstraps of monthly data. Bold type indicates coefficients that are significant at a five percent level and italics indicate coefficients significant at a ten percent level.

[A] Dependent Variable: Idiosyncratic Share of Portfolio Variance (Mean=44.72%)

		[1]	[2]
Feedback Measures	Cumulative outperformance relative to the market	**4.15**	**3.92**
		(0.32)	*(0.32)*
	Size of worst monthly stock portfolio return experienced		**-13.23**
			(1.55)
Age Effects: $\sqrt{\text{Account Age}}$		Y	Y
Log(Account Value)		Y	Y

[B] Dependent Variable: Monthly Turnover (Mean=5.06%)

		[1]	[2]
Feedback Measures	Cumulative increase in returns due to trades	**3.81**	**3.20**
		(0.39)	*(0.37)*
	Cumulative outperformance relative to the market		**0.75**
			(0.11)
	Size of worst monthly stock portfolio return experienced		**-14.41**
			(1.20)
Age Effects: $\sqrt{\text{Account Age}}$		Y	Y
Log(Account Value)		Y	Y

Continued on next page.

Table 2.8: *(Continued) Response of Individual Investor Behavior to Feedback*

[C] Dependent Variable: Disposition Bias - ln(PGR/PLR) x 100 (Mean=124.18)

		[1]	[2]
Feedback Measures	Cumulative increase in returns due to selling off gains versus losses	6.46	8.45
		(6.46)	*(6.56)*
	Cumulative outperformance relative to the market		**14.21**
			(3.44)
	Size of worst monthly stock portfolio return experienced		-17.63
			(17.57)
Age Effects: $\sqrt{\text{Account Age}}$		Y	Y
Log(Account Value)		Y	Y

earlier. This return to trades is then cumulated over the life of the account. This variable strongly predicts turnover, implying that trading profits strengthen the tendency to trade stocks frequently. This result is consistent with the findings of Linnainmaa (2011), who employs information on a set of high-frequency traders from Finland. The two variables from panel A also enter the turnover regression significantly.

It should be noted that the effect of recent trading profits on turnover may result in part from the disposition effect. If recent trading is profitable, then an account has tended to purchase winners which are more likely to be sold if the investor has disposition bias. Such sales, and subsequent purchases of replacement stocks, increase turnover.

Finally, in panel C we predict disposition bias using the returns to past sales of winners and losers. We calculate excess returns relative to the market index on stocks that each account sold, during the three month period following each sale, and compare the excess returns to losers sold relative to winners sold, weighting by the value of each sale and finally cumulating this measure over the life of the account. The idea of this measure is that if an account holds mean-reverting stocks, disposition bias tends to be profitable because winners sold underperform losers sold after the sale date, encouraging further disposition bias. If an account holds stocks that display short-term momentum, however, disposition bias tends to be unprofitable and may be discouraged by experience. This variable enters the regression with the expected sign, but is not statistically significant.

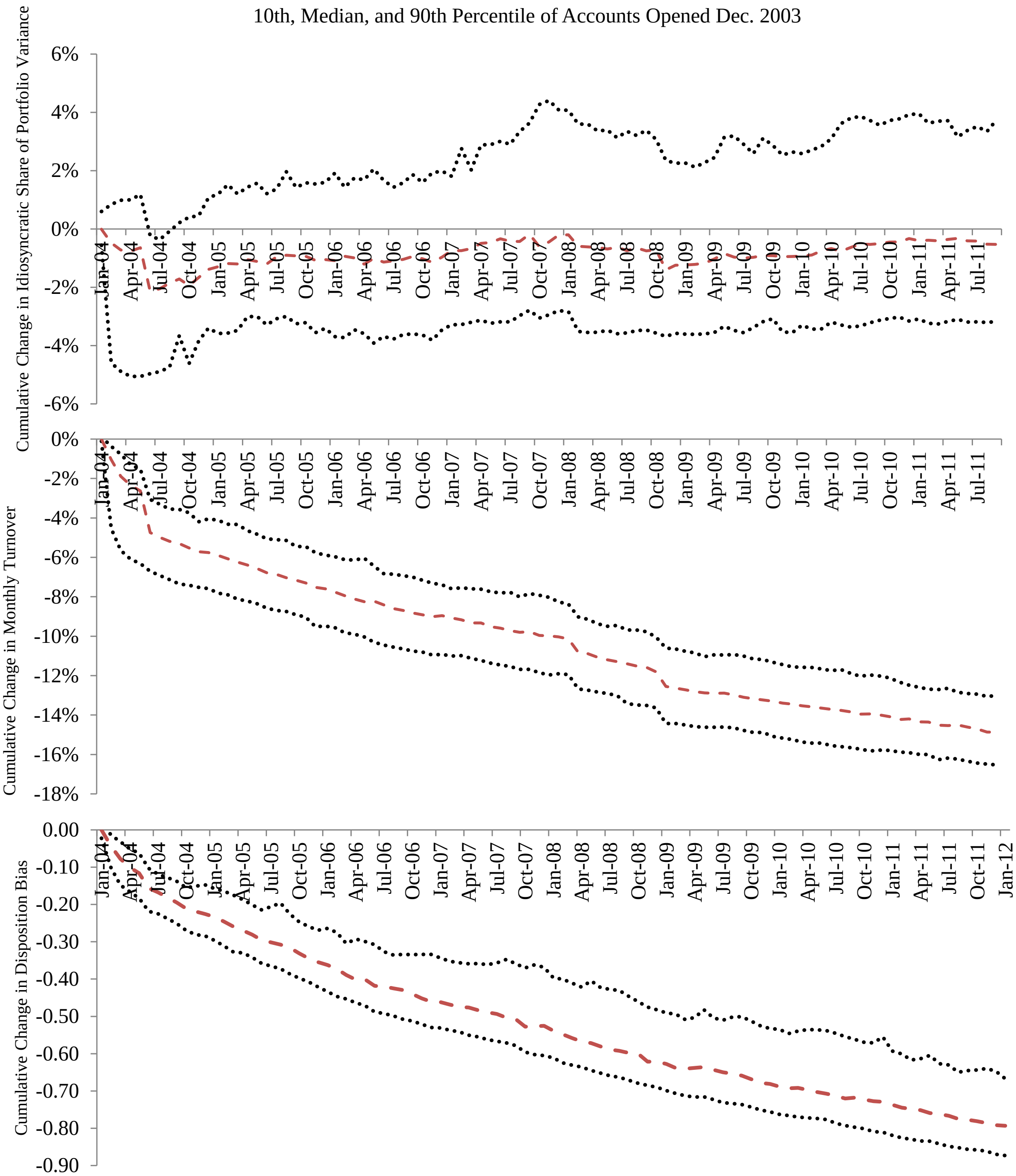
Figure 2.6 illustrates the relative importance of account age and investment experience in predicting each of our three investment behaviors. For all accounts that opened in December 2003, the figure shows the predicted behaviors from January 2004 through the end of the sample, using the all predictor variables except account value from the specification in column [2] of Table 2.8. The figure illustrates the median and the 10th and 90th percentiles of predicted behaviors. In both the disposition effect and turnover plots, the dominant influence of the age effect is clearly visible in the figure, but the spread in predicted behaviors across accounts is meaningful in the case of all investment behavior proxies. Declines in predicted behaviors occur rapidly at the beginning of the period, because of a strong early age effect and a market downturn in the spring of 2004. There is also a marked decline in the fall of 2008, again resulting from poor stock returns.

The empirical results of this section provide suggestive evidence of reinforcement learning among Indian equity investors. Our interpretation might be challenged if there is reverse causality, for example if skilled traders generate trading profits and continue to trade frequently in the future, or if certain investors specialize in holding mean-reverting stocks for which realizing gains and holding losses is a systematically profitable strategy. The presence of account level fixed effects in our specifications should significantly reduce concerns on this score, as the investor's average skill at trading should be absorbed by these account level effects. In addition, our regressions in Table 2.4 showed that turnover and disposition bias are associated with lower account returns, not higher returns as reverse causality would require.

2.5 Stock Returns and the Investor Base

In this section we change our focus from the performance of individual accounts to the performance of the stocks they hold, as predicted by the investor base of those stocks. This is somewhat analogous to the recent literature on the performance of mutual funds' stock

Figure 2.6: *Simulated Cumulative Change in Investor Behaviors from Age Effects and Feedback*



These figures are produced using age and feedback coefficients in the second column of Table 2.8 combined with the actual age and feedback received by individual investor accounts opened in December 2003. This feedack consists of cumulative market outperformance and worst monthly return experienced, return improvement due to trading (turnover plot), and return improvement due to selling gains versus losses (disposition bias plot).

picks, as opposed to the overall performance of the funds themselves (Wermers 2000, Cohen et al. 2010).

Table 2.9 uses Fama-MacBeth regressions to predict the returns of Indian stocks with at least 10 individual investors in our sample of individual accounts. Column 1 shows that the average age of the accounts that hold a stock predicts the return to that stock, consistent with the account-level results reported in Table 2.4. Column 2 adds information on the behavior of the investor base: the average share of idiosyncratic variance in the portfolios of the stock's investors, the turnover of these portfolios, and the disposition bias of the stock's investors. A high turnover investor base in particular predicts lower returns. The age effect, though somewhat diminished, remains significant.

Column 3 adds a standard set of stock characteristics to the regression. The book-market ratio and momentum enter positively, and stock turnover enters negatively, consistent with evidence from developed markets. The effect of account age in the investor base is now much weaker, but stocks with undiversified investors have lower average returns (significant at the 5% level), and stocks with disposition-biased investors have lower average returns. The effect of a high-turnover investor base remains negative, but it is smaller in magnitude because it is correlated with turnover in the stock itself.

The institutional ownership of stocks is included in Table 2.9 to addresses one possible concern about our finding of a positive age effect. Since institutional investors have gained market share over our sample period, stocks favored by such investors may rise in price just because they control more capital over time (Gompers and Metrick 2001). If older individual accounts are more like institutions, and hold similar stocks, this transitional effect may benefit long-established individual investors as well as institutions. However, this story is contradicted by the fact that in Table 2.9, the coefficient on institutional ownership is negative rather than positive.

Table 2.9: *Predicting Indian Stock Returns Using Characteristics of Investors*

The dependent variable is monthly stock returns from January 2004 through September 2011 for each of 3,614 stocks with at least 10 individual investors from our sample individual accounts. Stockholder account age is the average account age of investors in the stock in the given month. For behavioral characteristics of stockholders, we similarly use the average behavior across individual investors, where the behavior from a given individual investor is taken as the cumulative average of a cross-sectionally de-meaned measure of the behavior (idiosyncratic share of portfolio variance, monthly turnover, or ln(PGR/PLR)). Average investor account age and behavior measures, as well as market capitalization, book-market, momentum, turnover, and beneficial and institutional ownership share measures are converted to normalized rank form. The regressions below are carried out by the Fama MacBeth procedure, and a serial correlation adjustment (Newey West, 3 monthly lags) is applied. All coefficients are multiplied by 100 for readability, and statistical significance at the five and ten percent level are indicated by bold and italicized type respectively.

		[1]	[2]	[3]
Investor Characteristics	Account age	**1.85**	**1.21**	0.13
		(0.55)	*(0.57)*	*(0.26)*
	Idiosyncratic share of portfolio variance		0.93	**-0.63**
			(0.82)	*(0.29)*
	Portfolio turnover		**-1.75**	**-0.89**
			(0.51)	*(0.32)*
	Disposition bias		-0.11	-0.26
			(0.48)	*(0.32)*
Stock Characteristics	Market beta			0.22
				(1.22)
	Market capitalization			-1.51
				(1.56)
	Book-market			**3.84**
				(0.64)
	Momentum			**3.20**
				(0.63)
	Stock turnover			**-1.52**
				(0.39)
	Beneficial ownership			-0.67
				(0.42)
	Institutional ownership			-0.75
				(0.63)
	Ln(1+stock age)			0.06
				(0.11)

2.6 Conclusion

In this paper we have studied the investment strategies and performance of individual investors in Indian equities over the period from 2004 to 2012. We find strong effects of account age, the number of years since a particular account begins holding Indian stocks and appears in our dataset. Older accounts outperform younger ones, in part by tilting profitably towards value stocks and stocks of longer-established companies, but also by picking stocks that perform well after controlling for their characteristics. Older accounts also have lower turnover and a smaller disposition effect.

Our evidence also suggests that learning is important among Indian individual investors. Accounts that have experienced low returns relative to the market, and low returns in a single month, increase their diversification and reduce their turnover and disposition bias. Moreover, accounts that have experienced low returns from their trading decisions tend to reduce their turnover in the future, while poor returns associated with the disposition effect have an imprecisely estimated negative effect on future disposition bias. These results suggest that Indian individual investors learn, not only from the experience of stock market participation itself, but also from the returns generated by their investment behaviors.

If investment behaviors are related to investor financial sophistication, and if sophisticated investors are able to pick stocks with high expected returns, then the characteristics of a stock's investor base can be used to predict the stock's returns. We present evidence that this is the case, even controlling for the stock's own characteristics.

There are several interesting questions we have not yet explored, but plan to examine in the next version of this paper. We can ask whether the effect of experience on behavior is permanent, as implicitly assumed by our specification that predicts behavior using cumulative past returns, or whether the effect of experience decays over time as suggested by Agarwal et al. (2006, 2008). Second, we can explore whether the effect of experience on behavior varies with age, as might be the case if investors update priors about their skill or about the merits of selling winning positions, and gradually become more confident in their beliefs. Finally, we can ask whether all three of the behaviors studied in this paper can be aggregated into a single index of financial sophistication, as suggested by Calvet et al. (2009b).

Chapter 3

The Flow of Global Industry News

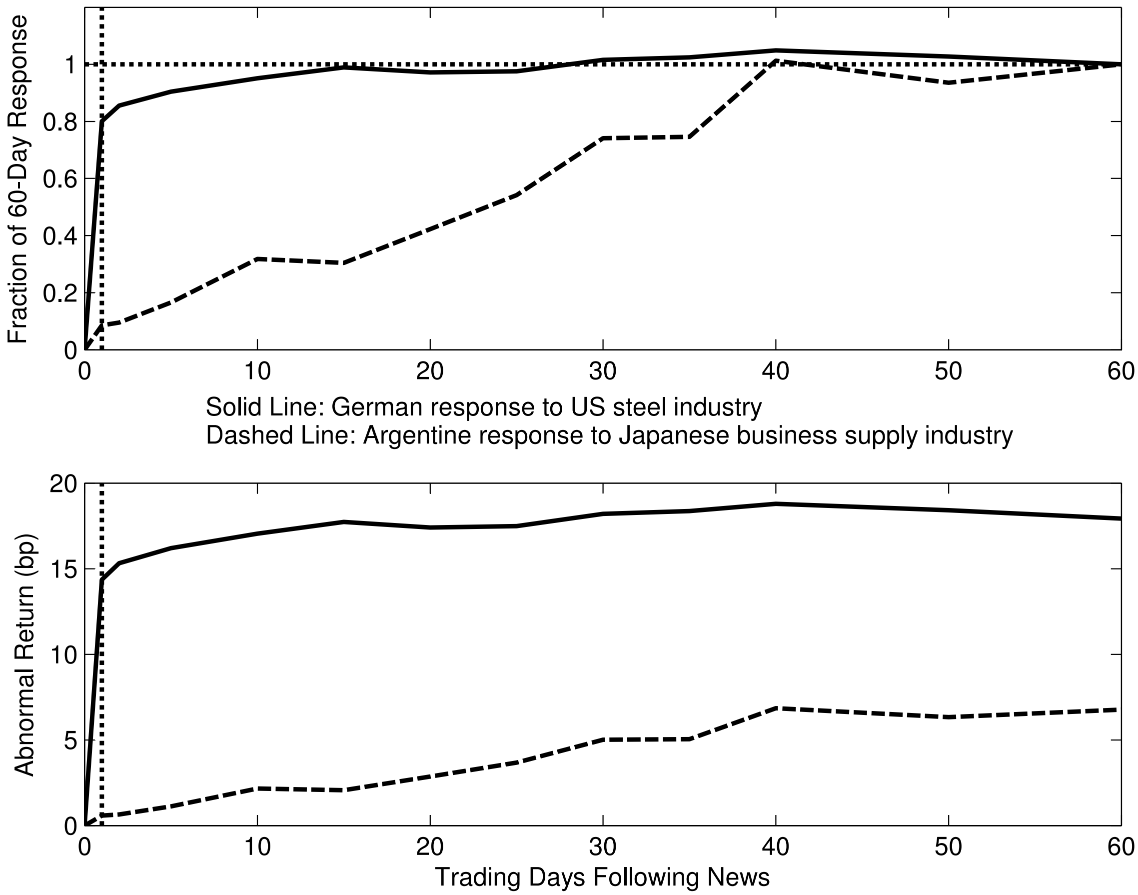
3.1 Introduction

Industry stock returns in a given country reflect news about demand, supply, and technological change which is often globally relevant. For example, high stock returns due to an unexpected increase in demand reflects good news for firms that sell their products in the same markets. Stock returns also signal of globally relevant information where it reflects changes in preferences and technology that are common across markets. A substantial literature shows that news reflected in stock returns is gradually incorporated in the prices of other stocks. Does the additional complexity of interpreting news from foreign markets and limited overlap of active investors across stock markets mean that news spreads even more gradually across borders than within borders? What properties of pairs of country-industry portfolios promote rapid incorporation of this cross-border news into prices? What do these findings suggest about trends in the relationship of industry returns in different markets?

In the next section, I review the literatures on gradual incorporation of news across stock prices and segmentation of equity markets. What follows is an endeavor to answer the questions above. The focus on industry level news is helpful as it allows usage of the significant variation in industry level cross-border linkages.

Figure 3.1 provides two examples of responses to cross-border industry news. These

Figure 3.1: *Responses to Industry News Between Two Selected Country-Industry Pairs*



The top plot scales responses by the magnitude of the 60 trading day response, while the bottom plot provides the response per standard deviation of industry news. Results are based on regression Equation 3.7.

estimates are produced from Equation 3.7, which is discussed in Section 3.4.

The dashed line in Figure 3.1 represents the estimated response of stock returns in the Argentine business supplies industry to one standard deviation of news in the Japanese business supplies industry. The Argentine response is very gradual. This inefficiency is not surprising given the limited means for industry information to flow between the Argentine and Japanese business supply industry portfolios. The two portfolios have no equity analysts in common or cross-listings with each other. Neither Argentines nor the Japanese hold significant equity stakes in each other's markets, and language may be a barrier to interpreting news. Furthermore, trading in the Argentine business supplies industry portfolio is a relatively unattractive proposition for international arbitrageurs, both due to the small size and liquidity of the Argentine business supplies industry and the expropriations risk inherent in investing in Argentina.

In other cases, responses to cross-border industry news are quite rapid. The solid lines in Figure 3.1 show that about 83% of the total response of German steel industry stocks to US steel industry stock return based news occurs within two trading days. Industry news travels between the two markets through the pricing of cross-listings such as Alcoa and the reports of several sell side equity analysts that cover both US and German steel industry stocks. The US and German stock markets also have a large base of investors in common.

These examples and other insights proceed from a methodical analysis of industry returns and the links between fundamentals and investors' likely information sets across country-industry pairs.

As a first step in the analysis, I construct daily excess industry returns spanning 47 industries in up to 55 countries over a period of 25 years. I define excess industry returns as the sum of responses to industry news generated across countries. Positive correlations of excess industry returns across countries show that industry news is typically relevant in several countries.

In Section 3.2, I detail the process by which the unobserved industry news is extracted from the set of excess industry returns. Conclusions in this paper rely on estimates of how the magnitude and speed of responses to industry news relate to a set of variables X, where these variables represent properties of the links between portfolios. It is important that the estimated relationships are not driven by arbitrary econometric assumptions. The procedure I use to extract industry news is designed to maintain a relationship between the news and X which is consistent with the observed covariances of excess industry stock returns.

In Section 3.3, I detail the global significance of industry news. Industry news generated by US markets triggers the largest stock return responses in foreign markets by a significant margin. More generally, I show news from major industry constituents and consumer markets generates greater responses. Responses to news are also greater between industry-country pairs that have historically had greater comovement in profitability. As a result, industry news has the greatest global impact in relatively homogeneous industries and industries with heavily traded products, such as computer software, steel, and various mining industries. There is little evidence that cross-border industry news is relevant in some local service industries, such as entertainment and health care.

In Section 3.4, I assess the speed with which markets respond to industry news from other countries. To do this, I regress excess industry returns over a range of horizons on industry news. Responses to cross-border industry news are gradual. On average, roughly half of the total response accumulates after the market has had a few trading days to incorporate the foreign news into prices. This drift accumulates primarily over a period of one to two months. Furthermore, the size of the drift relative to initial response is far greater when the industry news travels across borders than it is when the industry news originates within the same country.

I turn next to explanations for the significant variation across countries, industries, and time in the speed with which industry news is incorporated into prices. I measure this speed by the ratio of short-term to long-term response to news. To explain variation, I use the previously mentioned variables X. These variables capture three aspects relevant to the size and efficiency of responses: (i) the extent to which industry fundamentals are shared between countries, (ii) channels for and hindrances to information flows between the representative investors in industry portfolios, and (iii) the costliness of deploying arbitrage capital to correct underreaction in the responding portfolio.

Industry news generates stronger responses abroad when the news is from a large country or between countries and industries sharing strong fundamental connections such as trade. However, I find that strong fundamental links are not necessarily associated with more rapid responses; rational allocation of attention towards the most significant sources of news appears to play a limited role in explaining variation in response speed. In contrast, extensive information links, such as cross-listings, overlap in analyst coverage, and cross-border equity ownership are associated with more rapid cross-border responses. Responses of an industry portfolio are also faster where trading is relatively easy for large foreign investors, such as when the stocks are large and liquid, and where the country's institutions pose less risk to foreign investment. Results are robust to variation in the controls, fixed effects, and other methodological variations.

Section 3.5 studies how responses to cross-border industry news have changed over the years. While the long-run response to cross-border industry news has not changed much over time, the speed with which markets respond has increased dramatically. Emerging markets today respond to cross-border news about as rapidly as did developed markets in the early 1990s, and the magnitude of delayed response (drift) from developed markets is less than half of what it used to be. About half of this trend of improving efficiency is related to the growth of information links between stock markets and reduction of risks facing foreign investors over the past 25 years. Gains in response speed have disproportionately gone to countries which have improved the most along these lines.

Finally, I show that gradual responses to cross-border industry news has historically led to profitable trading strategies. An investor who buys stock in the industries in each country that have outperformed the most in other countries over the past month (a global industry momentum strategy) would have earned excess profits of about 8 percent per year. Profits remain a significant 4.5 percent per year after controlling for similarities between this strategy and the (within country) industry momentum strategy of Grinblatt and Moskowitz (1999). However, the profitability of the global industry momentum strategy has declined as the response speed to cross-border industry news has increased.

3.1.1 Related Literature

A broad literature in finance documents situations in which relevant information is only slowly reflected in stock prices. Stock prices, particularly of small stocks, underreact to earnings news (Bernard and Thomas 1989) and the information contained in accruals (Sloan 1996). Stocks all around the world exhibit momentum in performance over moderate horizons of a few months to a year (e.g. Jegadeesh and Titman 1993, Rouwenhorst 1998), which Hong, Lim, and Stein 2000 attribute to gradual diffusion of (firm-specific) information. Momentum of a similar magnitude also exists in returns of portfolios sorted by style, size, and industry (e.g. Moskowitz and Grinblatt 1999 and Lewellen 2000).

If stocks underreact to information reflected in their own returns, it is not surprising that they also underreact to information reflected in the returns of related assets. For example, returns on large and heavily traded stocks predict returns on small and thinly traded stocks (Lo and MacKinlay 1990 and Chordia and Swaminathan 2000), stock returns on customers predict stock returns of suppliers (Cohen and Frazzini 2008 and Menzly and Ozbas 2010), returns on stocks with lots of analyst coverage lead returns on stocks with less analyst coverage (Brennan, Jegadeesh, and Swaminathan 1993), returns on stocks with direct and simple relationships with news lead returns on stocks with complex relationships to the news (Cohen and Lou 2011), and stocks in some industries tend to lead the market (Hong, Torous, and Valkanov 2007). These findings are difficult to justify by means of rational risk-based models.

The same cognitive limitations and limits on arbitrage that lead to gradual diffusion of information within markets should also create gradual diffusion between markets. If anything, diffusion of information should be slower across borders. Investors are generally better informed about local investments than they are about distant or foreign investments (e.g. Coval and Moskowitz 2001 and Sonney 2009), and cross-border arbitrage may entail additional costs and complexity.

The literature on the speed and efficiency of responses to cross-border news (or returns) is less developed. Early papers tended to focus on the transmission of market returns across countries over short horizons and tended to conclude that responses were fairly efficient based on the observation that international responses taper off significantly after a few days (e.g. Eun and Shim 1989 and Copeland and Copeland 1998).[1] However, Rizova (2010) finds

[1] However, Becker, Finnerty, and Gupta 1990 show that Japan open-to-close returns are significantly correlated with the preceding US open-to-close returns.

that aggregate returns are predictable (over several months) by the lagged stock returns of trading partners, suggesting that investors pay insufficient attention to foreign country fundamentals. Albuquerque, Ramadorai, and Watugala 2011 build on this idea and suggest that trade credit is an important part of the mechanism generating cross-serial predictability of index returns. Unlike these papers, I study the pricing of industry-specific news. Industry level heterogeneity allows a more detailed analysis of the drivers of predictability across borders than is possible in previous research.

A much more developed literature studies market segmentation; the extent to which global stock markets do not appear to function as one large stock market with risk prices that are consistent across borders. Market segmentation is a clearly established fact. For example, studies have shown that "twin"stocks which share cash flows but have separate primary trading venues often trade at different prices (violating the law of one price) and co-move more strongly with returns in the market in which they are listed (Rosenthal and Young 1990 and Froot and Dabora 1999). A few of the ways segmentation has been measured include factor prices from a single factor (e.g. Errunza and Losq 1985 and Carrieri, Chaieb, and Errunza 2010) or multifactor/arbitrage pricing model (e.g. Cho, Eun, and Senbet 1986, Gultekin, Gultekin, and Penalti 1989, and Pukthuanthong and Roll 2009), the likelihood country risk is priced (Bekaert and Harvey 1995), comparing equity premium forecasts (e.g. Campbell and Hamao 1992), examining closed-end country fund premiums (Bonser-Neal et al 1990), or using industry valuation levels (Bekaert et al 2011). This project can be viewed as measuring segmentation in an alternative way. If two markets are integrated and behave as two halves of a single larger market, then industry news from either market should be incorporated equally rapidly.

3.2 Construction of Industry Portfolios, Returns, and News

3.2.1 Construction of Industry Portfolios and Excess Returns

The industries studied are from the SIC-based Fama French 49 industry classification. I use 47 of the 49 industries. The defence industry is omitted as it exists in too few countries for the news identification method used in this paper to work. The 49th industry is not used as it is a miscellaneous industry category which contains diversified conglomerates.

Use of this classification reflects a compromise. A more specialized classification potentially increases within industry similarities across countries and expands the cross-sectional variation in the data. However, greater specialization also results in smaller industry portfolios that have returns reflecting relatively more company specific information, contributing noise to the analysis. The Fama French classification system is commonly used, and provides strong within-industry return and fundamentals co-movement for a given number of industry portfolios (e.g. see Bhojraj, Lee, and Oler 2003 and Chan, Lakonishok, and Swaminathan 2007).

Stock returns data for the US are provided by the Center for Research in Security Prices (CRSP), while returns in other countries are from Compustat.[2] SIC codes from Compustat are used to sort the stocks into the Fama French industry portfolios. All foreign currencies are converted to US Dollars using historical exchange rates from Global Financial Database. I screen the securities, keeping only common share classes of equity that are the primary listings for a company. As a result, each company's stock is included in only one country's portfolio at a given point in time. I exclude the relatively few companies which are headquartered in a different country than the country in which their primary listing trades. Further data screens and adjustments are detailed in Appendix C.1. The data that remains for use after applying screens generally represents the majority of each country's market capitalization. Table C.1 lists the market capitalization covered by the equity data

[2]For a set of major stocks, I have verified that the data from Compustat Global and Datastream are virtually identical. Datastream generally has better coverage of the smallest securities, but these are all but irrelevant in value weight based analysis.

used for each of the markets at three points in time both in US dollars and as a percentage of the market's total capitalization according to the World Federation of Exchanges.[3]

I subtract a local return benchmark for each country from value-weighted industry returns to produce excess industry returns.[4] These returns reflect changing prospects for an industry relative to the broader economy. An advantage of removing a local return benchmark is that exchange rates enter benchmark and industry returns in much the same way, so my results cannot be attributed to features of or inefficiencies in the foreign exchange market. There is also no need for intra-day foreign exchange rate data.

A simple choice of benchmark is value-weighted market returns for each of the 55 markets. However, in smaller economies, market returns disproportionately reflect returns on certain industries. For example, high returns in the Finnish telecommunications industry around year 1999 result in high returns in the value-weighted Finnish stock market as a result of the disproportionately large telecommunications industry weighting. To address this, I construct industry-weight-adjusted market returns by weighting each (value-weighted) industry portfolio within a country in proportion to that industry's share of the global equity market. The resulting adjusted market returns are generally very similar to value-weighted market returns, with correlations averaging 0.96 across the 55 markets. I have also investigated using characteristic benchmarks instead (as in Daniel, Grinblatt, Titman, and Wermers 1997), but results are similar, and construction of reasonable benchmark portfolio returns in all but the largest markets faces challenges.

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[3]Coverage is lower in countries where many non-common equity listings (such as REITs) were removed, and where many of the listed companies are headquartered abroad (e.g. companies headquartered in China and trading in Hong Kong). Coverage levels are a bit lower on average in the early years. A comparison of reconstructed market returns with broader indices suggest this does not reflect survivorship, which would have only limited impact on the analysis I perform anyway. The daily frequency value-weighted returns that I use are unlikely to meaningfully correlate with firm survival, and if they do relate, it is more likely in a direction that biases towards findings of efficiency of response (i.e. fewer stocks survive following bad foreign returns).

[4]Use of equal weighted returns would be problematic since coverage of small stocks varies across countries in the data. Equal weighted returns are also significantly more volatile and less correlated across countries.

3.2.2 Construction of Industry News

One way to start is to define industry news using directly observed, relevant, and easily placed events, such as earnings surprises. Unfortunately, such events explain relatively little of the variation in excess industry returns. As a result, such analysis lacks sufficient power to identify causes of variation in the speed of responses to cross-border industry news. Instead, I associate the vector of daily industry i news from all countries c, $Z(i)$, with daily excess industry i stock returns, $R^{ex}(i)$, as in Equation (3.1) below. Defined this way, industry news reflects all information that appears in industry stock returns somewhere around the globe. This can be interpreted as a strength; results are more general than if industry news were associated with a set of easily identified events.

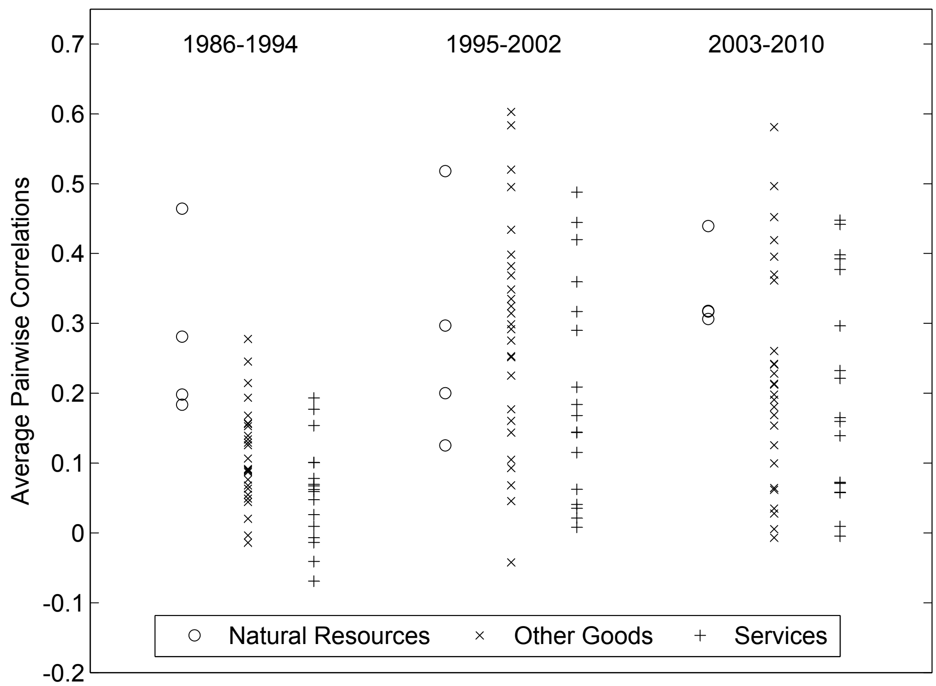
$$R^{ex}(i)_t = \Phi(0,i,t)Z(i)_t + \Phi(-1,i,t)Z(i)_{t-1} + \ldots, \text{ where } z_{c_1}(i) \perp z_{c_2}(i) \forall c_1, c_2 \tag{3.1}$$

The matrices Φ in Equation (3.1) determine how responsive excess industry returns in day t are to industry news generated in each market, with off-diagonal elements reflecting news' impact on stock returns abroad. The elements of Z are orthogonal; industry news is defined to be uncorrelated across countries. This can be interpreted as saying that each bit of information is priced first in a specific market, even if that information is ultimately reflected in the returns across many markets.

Figure 3.2 shows that cross-country correlations of quarterly excess industry returns are significant across a wide range of industries. This suggests that the global impact of industry news is economically important. Correlations are highest in natural resource industries (coal, oil, precious metals, non-metallic minerals). These industries are relatively homogeneous across countries and their output is heavily exported, so news generated in the natural resource industries has greater relevance across a range of countries. Correlations tend to be higher for goods than for services, with the lowest correlations found in services that cater primarily to customers within local markets, such as healthcare and recreation.

The difficulty in using Equation (3.1) is that only the excess industry returns, R^{ex}, are

Figure 3.2: *Cross-Country Correlations of Quarterly Excess Industry Returns for Five Large Developed Markets (the US, Japan, the UK, Germany, and France), by Industry over Three Time Periods*



The plotted correlations represent the average for a given industry and time-period across all pairs of the five markets and years for which industry portfolios exist.

observed. An infinite number of matrices Φ and vectors Z can fit. The remainder of this section describes an identification strategy designed so as not to bias the type of inferences made subsequently with the derived news terms.

To see why careful derivation of news is important, consider a simple two country example. Suppose Mexico (M) and the US (U) are the only two countries with steel industry portfolios, so that $Z(steel) = \begin{bmatrix} z_M(steel) & z_U(steel) \end{bmatrix}$. A simple decomposition of returns into industry news is given below. This news is denoted by $\tilde{Z}$ to distinguish it from the better justified news that will ultimately be constructed. The expression $E^*[r_U^{ex}(steel)_t | r_M^{ex}(steel)_t]$ represents the least squares best fit of US excess steel industry returns on Mexican steel industry returns, so $\tilde{z}_U(steel)_t$ is a regression residual.

$$\tilde{z}_M(steel)_t = r_M^{ex}(steel)_t$$

$$\tilde{z}_U(steel)_t = r_U^{ex}(steel)_t - E^*[r_U^{ex}(steel)_t | r_M^{ex}(steel)_t]$$

With this construction, a regression yields the decomposition below.

$$r_M^{ex}(steel)_t = 1.00\tilde{z}_M(steel)_t + 0.00\tilde{z}_U(steel)_t$$

$$r_U^{ex}(steel)_t = 0.06\tilde{z}_M(steel)_t + 1.00\tilde{z}_U(steel)_t$$

According to this decomposition, while Mexican news generates a response from US steel industry stocks (coefficient equals 0.06), US steel industry news causes no response in the Mexican stock market. This is an odd result. The US steel industry, both in terms of listed market capitalization and output, is about five times the size of the Mexican steel industry. Furthermore, while the exports to Mexico account for only 3% of US steel industry production, exports to the US account for about 20% of Mexican steel industry production.

Suppose I use this decomposition to estimate the relationship of exports to the magnitude of cross-border responses to news. Intuitively, cross-border responses should increase with the value of exports to the news generating country; news is more informative about demand facing an industry portfolio when it is generated in a larger consumer market for that industry. However, this example supports the presumably faulty conclusion that news from major export consuming countries is less important.

More generally, counterfactual conclusions can be obtained if the econometrician is free to create arbitrary relationships between variables (such as export share) and news. Ideally, conclusions about how variables relate to responses to industry news should only be driven by the structure of the stock returns data. I use covariances of excess industry returns to estimate how initial responses to industry news should relate to variables X used in subsequent analyses. I then construct industry news in a way that preserves these relationships.

The variables used later on in the paper and included in X are measures of fundamental and information links between industry portfolios, as well as measures of the obstacles facing arbitrageurs in each portfolio. Measures of fundamental links include: 1) the size of the industry portfolio generating the news, 2) the share of a country's industry exports sent to the country where the industry news originates, and 3) an estimate of the correlation in return on equity between portfolios. Measures of information links include: 1) the fraction of the portfolio's capitalization covered by sell-side equity analysts that provide coverage of stocks from both countries, 2) a (scaled) measure of cross-border equity holdings within each pair of countries, 3) the fraction of the portfolio's capitalization that is cross-listed in the other country, and 4) a dummy indicating whether the two countries share a primary language. Obstacles to arbitrage in the country responding to the news are measured by the 1) size of stocks in and 2) turnover of the responding portfolio, and 3) a professional assessment of the risks (such as expropriation) faced in particular by foreign investors in the responding country. In addition to these variables, X includes: 1) a constant term, 2) a measure of the extent to which trading hours overlap in the countries generating and responding to news, 3) an adjacent country dummy, 4) a measure of cultural distance, 5) the excess return volatility of the country responding to the news, and 6) the volatility of the news itself. The construction of these variables is detailed in Appendix C.2. A correlation matrix for the variables in X is given in Table 3.1.

Table 3.1: *Correlation Matrix and Standard Deviations of Attributes of Industry Portfolio Pairs*

Standard deviations of each variable are given along the diagonal of the table, and below diagonal elements give pairwise correlations between the variables across pairs of country-industry portfolios and years.

Variable		[sz]	[vol]	[trade]	[roe]	[lang]	[xanalyst]	[xhold]	[xlist]
Attributes of Portfolio Where the Industry News is From ($pf(c)$)									
Size of $pf(c)$	[sz]	**1.00**							
Log($\sigma(z(i,c))$)	[vol]	-0.35	**0.45**						
Attributes Related to Fundamental Ties between Industry Portfolios									
Exports from $c1$ to c	[trade]	0.32	-0.18	**1.00**					
(Return on Equity)	[roe]	0.06	0.01	0.04	**1.00**				
Attributes Related to Information Channels between Industry Portfolios									
Common Language	[lang]	0.08	-0.05	0.13	0.02	**0.49**			
Analyst Overlap Between Portfolios	[xanalyst]	-0.03	-0.01	0.33	0.08	0.14	**0.22**		
Cross-Border Equity Holdings Within Pair	[xhold]	0.17	-0.08	0.41	0.11	0.34	0.51	**1.00**	
Industry Cross-Listings Between Pair	[xlist]	0.15	-0.07	0.14	0.09	0.15	0.18	0.25	**0.09**
Attributes of the Portfolio Responding to the News ($pf(c1)$) Related to Arbitrage Costs									
Size of Stocks in $pf(c1)$	[sz_resp]	-0.05	-0.11	-0.01	0.15	0.06	0.23	0.25	0.26
Log($\sigma(R^{ex}(i,c1))$)	[v_resp]	0.04	0.30	0.01	-0.06	-0.07	-0.08	-0.16	-0.14
Turnover of $pf(c1)$	[turn]	0.01	0.01	0.09	0.01	-0.04	0.03	0.16	0.08
Investment Risk	[risk]	0.06	-0.07	-0.04	-0.06	-0.08	-0.25	-0.51	-0.04
Other Country Pair Attributes									
Overlap in Trading Hours	[hrs]	-0.12	0.04	0.35	0.03	0.08	0.56	0.29	0.10
Adjacent Country	[adj]	-0.04	0.01	0.31	0.02	0.08	0.39	0.21	0.14
Cultural Distance	[cult]	0.03	0.01	-0.09	-0.05	-0.14	-0.22	-0.18	-0.11

Variable		[sz_resp]	[v_resp]	[turn]	[risk]	[hrs]	[adj]	[cult]
Attributes of the Portfolio Responding to the News ($pf(c1)$) Related to Arbitrage Costs								
Size of Stocks in $pf(c1)$	[sz_resp]	**1.00**						
Log($\sigma(R^{ex}(i,c1))$)	[v_resp]	-0.51	**0.52**					
Turnover of $pf(c1)$	[turn]	0.16	-0.20	**0.11**				
Investment Risk	[risk]	-0.23	0.10	0.01	**1.00**			
Other Country Pair Attributes								
Overlap in Trading Hours	[hrs]	0.03	0.00	-0.04	-0.09	**0.42**		
Adjacent Country	[adj]	0.05	-0.04	0.02	-0.02	0.40	**0.28**	
Cultural Distance	[cult]	-0.10	0.09	0.02	0.08	-0.20	-0.19	**1.00**

Now, let us return to the US-Mexico steel industry example. This example has the advantage that the American and Mexican stock markets are open at the same time. Appendix C.3 discusses how the method developed here is generalized to apply to markets that trade asynchronously.

The relationship of returns and news in this example is taken from Equation (3.1) and given as Equation 3.2 below.

$$\begin{bmatrix} r^{ex}_M(steel)_t \\ r^{ex}_U(steel)_t \end{bmatrix} = \begin{bmatrix} \phi_{M,M}(0, steel, t) & \phi_{M,U}(0, steel, t) \\ \phi_{U,M}(0, steel, t) & \phi_{U,U}(0, steel, t) \end{bmatrix} \begin{bmatrix} z_M(steel)_t \\ z_U(steel)_t \end{bmatrix} + \begin{bmatrix} \phi_{M,M}(-1, steel, t) & \phi_{M,U}(-1, steel, t) \\ \phi_{U,M}(-1, steel, t) & \phi_{U,U}(-1, steel, t) \end{bmatrix} \begin{bmatrix} z_M(steel)_{t-1} \\ z_U(steel)_{t-1} \end{bmatrix} + \dots \tag{3.2}$$

Next, I use X to estimate initial response coefficients as in Equation (3.3) below. I also scale news and coefficients so that the loading of a portfolio's response to its own news equals one.

$$\begin{gathered} \phi_{M,U}(0, steel, t) = \beta(steel, y(t)) X(steel, M, U, y(t)) + \varepsilon(0, steel, M, U)_t \\ \phi_{U,M}(0, steel, t) = \beta(steel, y(t)) X(steel, U, M, y(t)) + \varepsilon(0, steel, U, M)_t \\ \phi_{M,M}(0, steel, t) = \phi_{U,U}(0, steel, t) = 1 \end{gathered} \tag{3.3}$$

The coefficients $\beta(steel, y(t))$ give the extent to which X predicts day t responses to news in the steel industry in year $y(t)$. The ε terms are assumed to be idiosyncratic. I also assume here that responses to old news are zero; $\Phi(\tau, steel, t) = 0$ for $\tau < 0$. This simplifying assumption has an immaterial impact on the estimation of β; delayed responses to older news play a negligible role in the covariances of day t stock returns.

With these assumptions about the structure of stock return responses to industry news and recalling that $z_M(steel)$ and $z_U(steel)$ are uncorrelated, the expected covariance of Mexican and US excess steel industry is given by Equation (3.4) below.

$$E[r_M^{ex}(steel)_t r_U^{ex}(steel)_t|X] = \beta(steel, y(t))X(steel, M, U, y(t))\sigma^2_{z_U(steel)_t} + \beta(steel, y(t))X(steel, U, M, y(t))\sigma^2_{z_M(steel)_t} \tag{3.4}$$

In the simple example there are only two countries used, but in actuality I use all countries for which the industry portfolio comprises at least one percent of the global market capitalization for that industry in the given year. Ignoring small portfolios in the derivation of industry news has minimal impact. Subsequent results suggest that the impact of industry news on stock prices in other countries is strongly predicted by the size of the portfolio producing the news.

Suppose N_c countries are included for a given industry and year. There are $N_c(N_c-1)/2$ excess industry return covariances which can estimated.[5] Variance terms add another N equations. The unknowns consist of the 16 elements of $\beta(i, y)$ and N variances of industry i news $z_c(i)$. When N_c is large enough for the given industry and year to provide at least 10 over-identifying equations, then I estimate $\beta(i, y)$ separately by year and industry. This condition, which is usually met where $N_c \geq 6$, is provided to minimize the risk of extreme over-fitting. If the cross-section is smaller, I add adjacent years of data for the industry, allowing only the intercept term in β and volatility of industry news to vary across years, until there are at least 10 over-identifying equations.

Allowing β to vary across industries and years allows greater flexibility in the way in which the structure of responses to industry news relates to X, reducing the role of econometric assumptions. As a result, β is usually estimated quite imprecisely for a given industry and year. However, the mean β has several statistically significant elements as shown in Table C.2. I do not detail the estimates of β further here, as they are by construction reflected in the subsequent analysis of short run responses to cross-border news. However, the typical estimate of β suggests that responses of Mexican steel industry stock returns to

[5]Due to asynchronous trading (discussed in Appendix C.3), I obtain a further $N_c(N_c-1)/2$ equations from covariances of day t and $t-1$ returns.

US steel industry news should be significantly larger than the responses of US steel industry stock returns to Mexican steel industry news.

Once β is estimated, providing an estimate of Φ, I derive industry news according to Equation (3.5) below. The set $\hat{\Phi}^{-1}R^{ex}$ is nearly orthogonal, and by construction preserves the relationships given by $\hat{\beta}$. Equation (3.5) uses a singular value decomposition to define industry news as the orthogonal set which is closest to $\hat{\Phi}^{-1}R^{ex}$ in a Euclidean sense.[6]

$$Z(steel) =^{argmin}_{Z^*(steel)} ||Z^*(steel) - \hat{\Phi}^{-1}(0, steel, t)R^{ex}(steel)|| \text{ s.t. } z_M(steel) \perp z_U(steel) \tag{3.5}$$

$$\hat{\Phi}^{-1}(0, steel, t) = \begin{bmatrix} 1 & \hat{\beta}(steel, y(t))X(steel, M, U, y(t)) \\ \hat{\beta}(steel, y(t))X(steel, U, M, y(t)) & 1 \end{bmatrix}^{-1}$$

Figure 3.3 provides a first look at how excess industry stock returns compare with the constructed industry news, taking the US steel industry as an example. The difference between US returns and US news primarily reflects the response of US steel industry stock returns to steel industry news from other countries. In general, the local industry news is the primary driver of excess industry returns, but foreign industry news generates a noticeable response in mid-2009.

Table 3.2 generalizes this comparison of industry news and excess industry returns. Correlations between excess industry returns and industry news are typically close to one. This results primarily from low cross-country correlations in daily excess industry returns. The table also shows that industry news and excess industry stock returns are most volatile around the "Dot-Com Bubble"and the Financial Crisis.

Table 3.2 shows that the correlation of industry news varies over time. It also varies significantly across countries and industries. This variation is driven by cross-sectional and

[6]In a large sample, if the structure imposed by Equation (3.3) were exactly true, then $\hat{\Phi}^{-1}R^{ex}$ would be an orthogonal set. As is, X explains much of the contemporaneous covariation in excess industry stock returns, so the mean correlation between $\hat{\Phi}^{-1}R^{ex}$ and the resulting Z exceeds 0.995.

Figure 3.3: *Excess US Steel Industry Stock Returns and US Steel Industry News, January 2009 through November 2010*

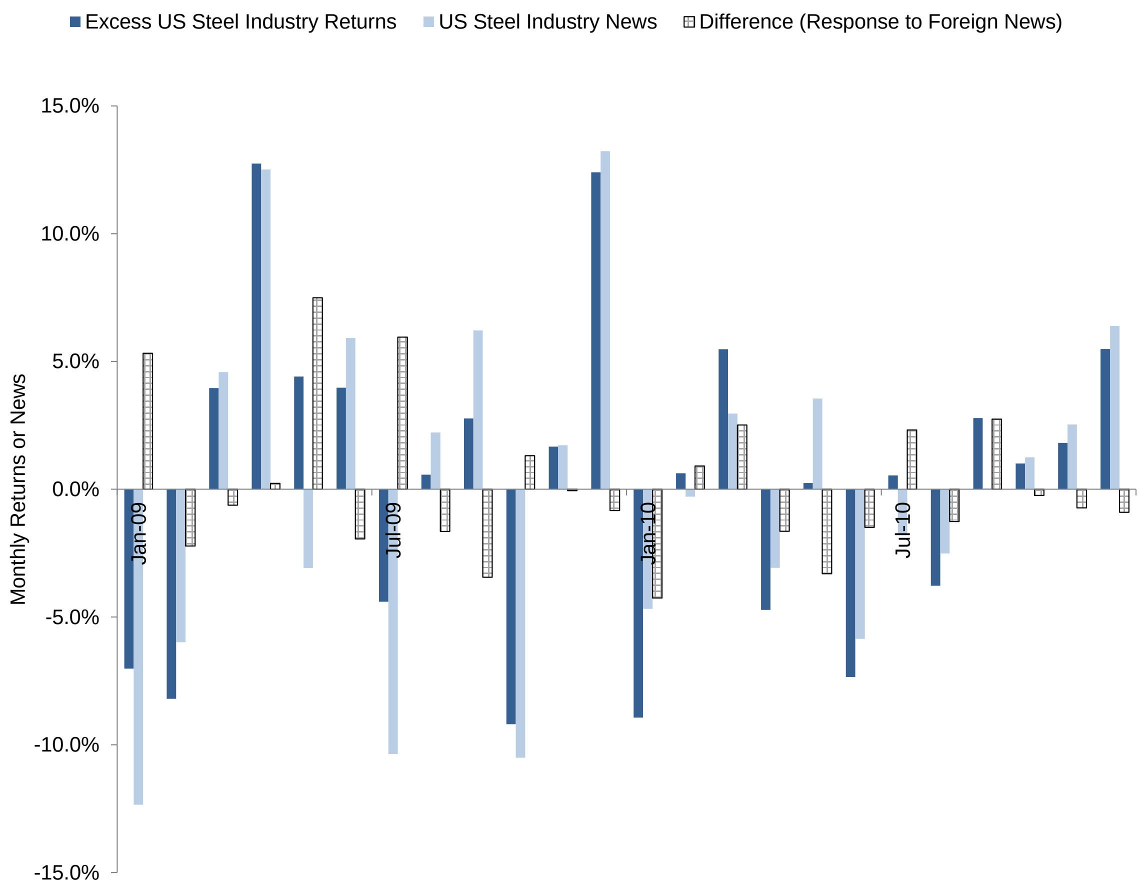


Table 3.2: *Industry News Volatility and Correlations with Excess Industry Returns*

Distributions are measured across all industry portfolios which represent at least one percent of the global market capitalization for the given industry in the given year.

		$\sigma(z)$			$\rho(R^{ex}, z)$	
Year	10th	Median	90th	10th	Median	90th
1986	0.60%	1.25%	2.02%	0.968	0.994	0.999
1987	0.73%	1.27%	2.25%	0.971	0.993	0.999
1988	0.53%	0.97%	1.84%	0.971	0.994	0.999
1989	0.51%	0.93%	1.64%	0.977	0.993	0.998
1990	0.62%	1.04%	2.06%	0.972	0.992	0.998
1991	0.55%	0.96%	1.69%	0.971	0.992	0.998
1992	0.57%	1.03%	1.94%	0.979	0.992	0.998
1993	0.56%	0.99%	1.85%	0.972	0.992	0.998
1994	0.51%	0.97%	1.72%	0.977	0.990	0.997
1995	0.57%	0.95%	1.83%	0.978	0.992	0.997
1996	0.56%	0.96%	1.70%	0.971	0.991	0.997
1997	0.76%	1.23%	2.18%	0.972	0.989	0.996
1998	0.95%	1.56%	2.59%	0.959	0.987	0.995
1999	1.07%	1.58%	2.55%	0.960	0.987	0.995
2000	1.30%	1.92%	2.92%	0.896	0.976	0.994
2001	1.03%	1.58%	2.53%	0.898	0.979	0.995
2002	0.87%	1.46%	2.27%	0.913	0.980	0.994
2003	0.75%	1.23%	1.90%	0.937	0.984	0.995
2004	0.59%	0.97%	1.66%	0.942	0.985	0.995
2005	0.55%	0.88%	1.49%	0.957	0.988	0.995
2006	0.59%	0.98%	1.69%	0.936	0.985	0.995
2007	0.66%	1.10%	1.87%	0.931	0.983	0.994
2008	1.15%	1.66%	2.87%	0.898	0.973	0.990
2009	0.95%	1.42%	2.33%	0.907	0.977	0.993
2010	0.64%	1.01%	1.63%	0.937	0.982	0.993

time-series differences in the way industry stock returns respond to cross-border industry news. In the rest of the paper, I investigate how these differences relate both to links in industry fundamentals and investor information across countries.

3.3 Impact of Cross-Border Industry News

To gauge the impact of industry news across borders, I run regressions of cumulative excess industry returns on industry news from other countries. These regressions, given by Equation 3.6 below, are run over the set of all country pairs, industries, and years y.[7] In Equation 3.6, $r^{ex}_{c1}(i)_{t:t+\tau}$ represents excess returns from industry i country $c1$ over days t through $t+\tau$, and $z_{c2}(i)_{t^*}$ is industry i news from country $c2$ on day t^*. Day t^* is the most recent trading day in $c2$ which ended before the close of day t trading in $c1$.

$$r^{ex}_{c1}(i)_{t:t+\tau} = b(i, c1, c2, y, \tau) z_{c2}(i)_{t^*} + \varepsilon(i, c1, c2, \tau)_t \tag{3.6}$$

I set $\tau = 1$ or $\tau = 30$. By the end of $t+1$, all industry news from $c2$ on day t^* should be incorporated into prices if markets are efficient with respect to cross-border industry news.[8] If markets respond slowly, measuring returns through day $t+30$ provides a more complete and less downwards biased, but less precisely estimated measure of the impact of industry news.

In Table 3.3, I use Equation (3.6) to list the industries from which industry news has the greatest impact on industry stock returns in other countries. I report the average coefficient b by industry, applying equal weight to each year worth of observations and weighting coefficients within each year in proportion to the responding ($c1$) country's market

[7] Adding a constant term to Equation 3.6 has minimal impact.

[8] A more stringent measurement would be to measure only the impact on opening prices on day t for cases where the foreign market closes before the local market opens (or opening prices on day $t+1$ where the foreign market opens after the local market closes), or the closing prices on day t where the foreign market closes while the local market is open. However, opening price data is of limited availability, and microstructure issues (such as differences in how opening prices are determined) complicate interpretation.

capitalization.[9] In the third column, I average coefficients scaled by the standard deviation of the industry news to provide a sense of the economic magnitude of the responses.

The industries where news has greatest impact in other countries are where output is heavily exported (such as control equipment and computers) or relatively homogeneous (such as oil, gold, and utilities). In these industries, news for companies of one country is more informative about consumer demand and changes in technology that affect companies in other countries. The 30 day response coefficients for the top 10 industries are quite sizable, ranging from approximately 0.10 to 0.18, though true response coefficients for the top 10 are likely a bit lower as coefficients are estimated. In contrast, industries that generate news of minimal impact abroad, such as the personal services industry, are relatively heterogeneous across countries. I do not provide an analogous list of the bottom 10 industries as the estimated coefficients are statistically indistinguishable.

In Table 3.4, I instead average the b across news originating countries $c2$. This table shows that large markets and economies generate industry news with the greatest impact on excess industry stock returns abroad. News from large industry portfolios reflects relatively less company specific news and relatively more news of industry-wide relevance. News from (large) countries with greater demand for industry output is more relevant to exporting companies. Industry news from the United States has about the same impact on excess industry stock returns in other countries as does news from the next four countries combined (United Kingdom, Japan, Germany, and China), which is consistent with the much larger size of the United States economy and stock market throughout most of the time series. I do not provide a longer list of rankings of countries by impact of industry news, as the standard error of the coefficient estimates is large relative to the magnitude of the estimated response coefficients, and the ranking becomes meaningless.

Figure 3.4 generalizes the observations of Tables 3.3 and 3.4 by plotting average response coefficients b to cross-border industry news for groups defined by attributes of the country

[9]The averages are taken across only the largest five news producing portfolios for the given industry and year. This is done to improve comparability across industries; some industries are present in many minor markets while others are not.

Table 3.3: *Ten Industries with News Generating the Greatest 30 Day Responses in Other Countries' Stock Markets*

Response coefficients above are the average b (from Equation (3.6): $r^{ex}_{c1}(i)_{t:t+\tau} = b(i, c1, c2, y, \tau) z_{c2}(i)_{t^*} + \varepsilon(i, c1, c2, \tau)_t$) for the given industry across the largest five news producing portfolios for the industry in the given year. In the computation, equal weight is applied to each year worth of observations and coefficients within each year are weighted in proportion to the responding ($c1$) country's market capitalization. The third column instead takes averages of coefficients scaled by the standard deviation of the industry news. Standard errors are provided in parentheses.

	Response Coefficient		30 Day Response (bp)
Industry Name	30 Day ($\tau = 30$)	1 Day ($\tau = 1$)	per +1 S.D.
Gold/Precious Metals	0.179	0.201	42.6
	(0.050)	(0.024)	(9.6)
Utilities	0.177	0.063	12.5
	(0.066)	(0.009)	(3.7)
Measuring & Control Eq.	0.163	0.021	13.7
	(0.041)	(0.009)	(3.7)
Machinery	0.141	0.037	10.0
	(0.032)	(0.009)	(2.2)
Petroleum & Nat. Gas	0.134	0.144	14.2
	(0.027)	(0.014)	(2.8)
Pharmaceuticals	0.129	0.092	12.3
	(0.028)	(0.014)	(2.5)
Non-Metallic Indus. Metals	0.122	0.117	15.4
	(0.029)	(0.014)	(3.7)
Chemicals	0.110	0.040	8.8
	(0.023)	(0.006)	(1.9)
Food Products	0.101	0.079	9.9
	(0.027)	(0.012)	(2.4)
Computer Hardware	0.096	0.057	10.0
	(0.036)	(0.011)	(4.1)

Table 3.4: *Five Countries with Industry News Generating the Greatest 30 Day Responses in Other Countries' Stock Markets*

Response coefficients above are the average b (from Equation (3.6): $r^{ex}_{c1}(i)_{t:t+\tau} = b(i, c1, c2, y, \tau)z_{c2}(i)_{t^*} + \varepsilon(i, c1, c2, \tau)_t)$ for the given news originating country ($c2$). In the computation, equal weight is applied to each year worth of observations and coefficients within each year are weighted in proportion to the responding ($c1$) country's market capitalization. The third column instead takes averages of coefficients scaled by the standard deviation of the industry news. Standard errors are provided in parentheses.

	Response Coefficient		30 Day Response (bp)
Industry Name	30 Day ($\tau = 30$)	1 Day ($\tau = 1$)	per +1 S.D.
United States	0.159	0.081	15.8
	(0.012)	(0.004)	(1.0)
United Kingdom	0.037	0.020	5.0
	(0.012)	(0.004)	(1.6)
Japan	0.037	0.021	4.4
	(0.014)	(0.004)	(1.5)
Germany	0.027	0.011	3.1
	(0.011)	(0.003)	(1.3)
China	0.021	0.007	2.8
	(0.012)	(0.004)	(1.6)

pairs and industries. The solid blue part of each bar represents the response coefficient corresponding to returns from day t through day $t+1$, while the entire bar represents the response coefficient through day $t+30$. Across groups, the initial response to industry news (the blue part of the bars) accounts for only about half of the 30 day response. Given that this proportion is similar across most of the groups plotted in Figure 3.4, other variables need to be considered to provide an explanation for delay in stock price responses. This is the focus of the next section.

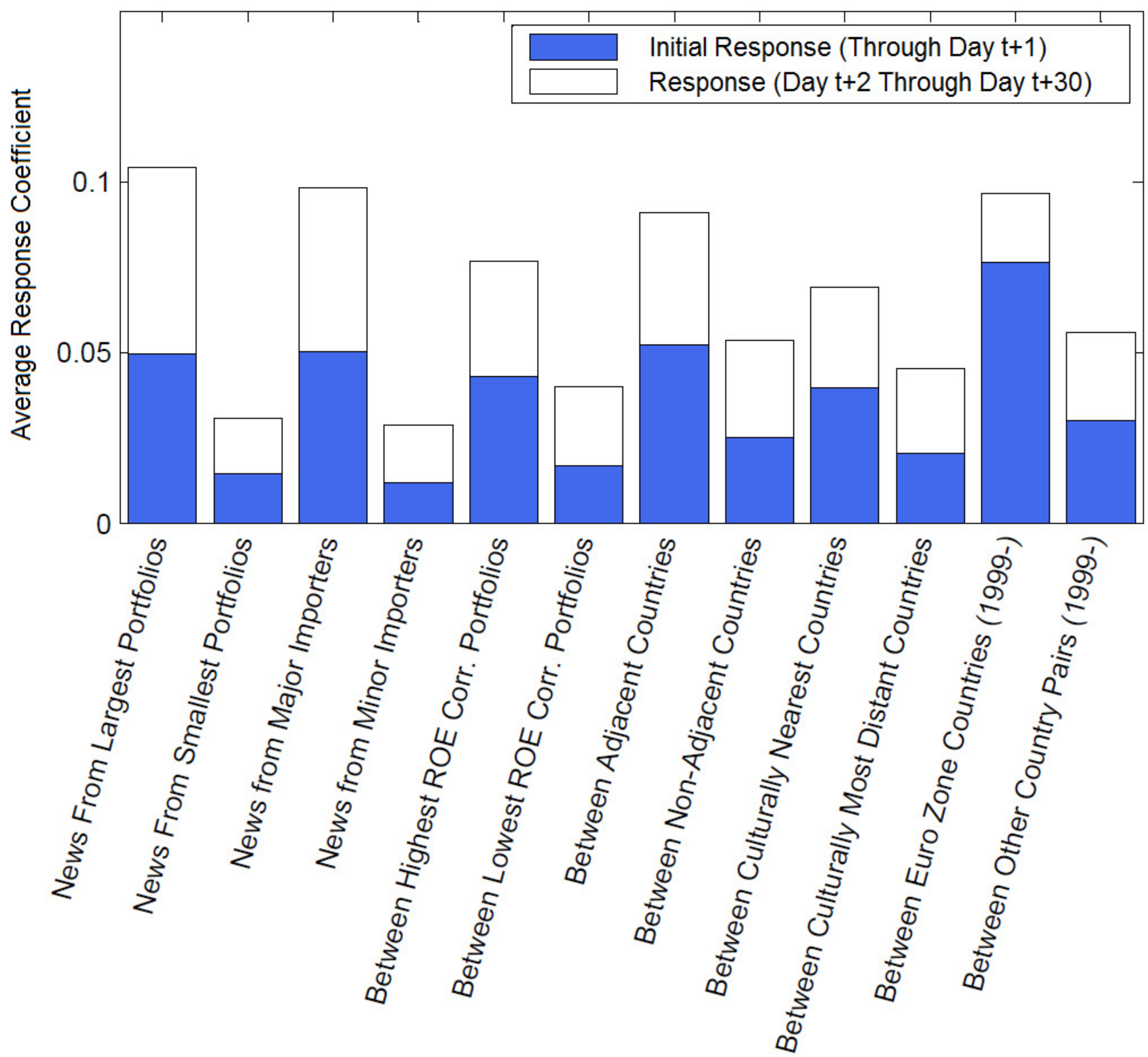
A number of sensible patterns emerge in Figure 3.4. The first two bars show that industry portfolios in the top quintile by market capitalization produce news with more than three times the impact on stock returns abroad as portfolios in the bottom quintile, with 30 day response coefficients averaging larger than 0.10 versus about 0.03 for news from the smallest portfolios.[10] The second two bars show a similar sized difference between country pairs sorted based on the fraction of the responding country's industry output imported by the country generating the news. The third pair of bars demonstrate that industry news has much greater impact where industry fundamentals have comoved more strongly across borders as measured by estimates of correlations in industry return on equity. The remaining three pairs of bars show that industry news impact is on average greater from adjacent countries, between countries that have less "cultural distance"as measured by the World Values Survey, and between countries in the Euro zone.

The strength of the conclusions drawn from Figure 3.4 are limited by confounding correlations in the chosen attributes. For example, large portfolios tend to be found in large countries that are major end markets for exporters. I disentangle competing explanations for the impact of industry news across borders in a multivariate analysis in the next section. However, it remains the case that each of the variables in Figure 3.4 is shown to have incremental explanatory power for the impact of industry news on stock prices across borders.[11]

[10] The smallest industry portfolios included in the bottom quintile represent at least one percent of the global market capitalization for the given industry in the given year.

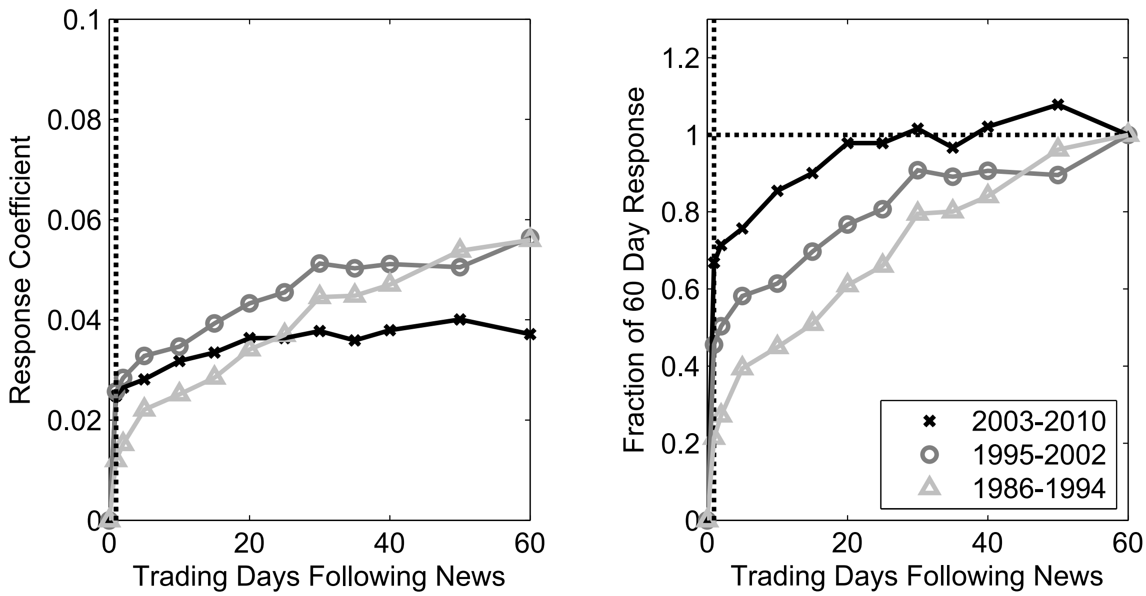
[11] However, the incremental role of cultural distance and the Euro zone and adjacent country dummies on

Figure 3.4: *Average One and 30 Day Response of Excess Industry Stock Returns to Industry News from Across Country Borders*



Responses are averaged across groups sorted by attributes of the portfolio where the news is from and the pair of portfolios between which the news is flowing. Results are based on the estimated coefficients b from Equation 3.6: $r^{ex}_{c1}(i)_{t:t+\tau} = b(i, c1, c2, y, \tau) z_{c2}(i)_{t^*} + \varepsilon(i, c1, c2, \tau)_t$. The solid blue portion of each bar represents the response coefficient from regressions of excess industry returns from trading days t through $t+1$ (i.e. $\tau = 1$) on day t^* industry news, where t^* is the most recent trading day in $c2$ which ended before the close of day t trading in $c1$. The total height of each bar represents the response coefficient from regressions of excess industry returns from trading days t through $t+30$ (i.e. $\tau = 30$) on day t industry news. The largest portfolios (by market capitalization), major importers, highest estimated return on equity correlations, and greatest cultural distance categories reflect the average responses from country-pair-industry years in the top quintile under the given measure and vice versa. Construction of these measures is detailed in Appendix C.2.

Figure 3.5: *Average Response of Excess Industry Stock Returns to Industry News Across Country Borders, by Time Period*



Results are based on estimated response coefficients b from regression Equation 3.6: $r^{ex}_{c1}(i)_{t:t+\tau} = b(i, c1, c2, y, \tau) z_{c2}(i)_{t^*} + \varepsilon(i, c1, c2, \tau)_t$. Regressions are run over time horizons extending from day t out to up to 60 trading days following the news ($\tau = 1$ to 60), where t^* is the most recent trading day in $c2$ which closes prior to the end of day t trading in $c1$. Left plot: The average of b is across all country pairs, industries, and years within each of three time periods. Right Plot: Equal to the left plot scaled by the average response coefficient over 60 trading days ($\tau = 60$).

3.4 Responsiveness of Stock Returns to Cross-Border Industry News

Figure 3.5 plots the average (excess industry stock return) response coefficients over three periods of time to industry news from across country borders. These coefficients are the b in regression Equation 3.6 used in the last section. The curves correspond to regressions of excess industry stock returns on industry news where the returns are accumulated from day t through various horizons out to day $t + 60$ ($\tau = 1$ to 60). The left plot in the figure shows the average response coefficients. The right plot of the figure scales these coefficients by the average response coefficient at $\tau = 60$ so that the speed at which markets incorporate industry news can be easily compared across time periods.

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determining response magnitudes is modest.

The dashed line near the vertical axis reflects responses as of the end of day $t + 1$, the measure of initial response. If markets are efficient with respect to cross-border industry news, day t industry news should be incorporated into prices by the end of day $t + 1$; the curves should not be below this dashed line after this date.

The typical response to industry news from other countries is quite inefficient over the three month horizon plotted. The delayed part of the response (occurring after $t + 1$) is typically of the same order of magnitude as the the initial response. As can be seen from the figure, this conclusion is unchanged if the initial response were redefined to include an extra day or two of trading; the response on day t is the strongest by a large margin.

The response gradually tapers off. After 60 trading days, there is no evidence of significant continuing response to the news.[12] Going forward, I use responses at a horizon of 30 trading days as a proxy for the total response. This reduces measurement error, and most (generally at least 80%) of the response is completed within 30 trading days.[13]

Table 3.5 reports statistics corresponding to Figure 3.5, along with standard errors. The inefficiency and the improvement in response speed over time are statistically and economically significant. Over time, the delayed portion of the response has fallen by half from about 76% to 38%. The improvement would be even more stark if the changing composition of markets in the dataset were taken account of at this stage; data from more recent years have a higher proportion of smaller developing markets which I show respond less efficiently. I discuss how responses to industry news from other countries have changed over time in more detail in Section 3.5.

Given the abundance of research on gradual diffusion of information within a market, a

[12] This drift horizon is comparable to that found from the lag effect of returns on the smallest quintile of stocks to market returns (documented by Lo and MacKinlay 1990), “complicated trades”(Cohen and Lou 2011), and the between industry lead-lag effects documented by Hong, Torous, and Valkanov (2007). Industry momentum documented by Moskowitz and Grinblatt 1999 has similar duration when formed on only one month’s lagged industry returns. Trade related momentum documented by Rizova 2010 appears to last somewhere between two and eight months, but this effect represents purely mispricing across (not within) markets.

[13] There is greater evidence of drift in the 30 to 60 day horizon in earlier time periods (see the right hand side plot of Figure 3.5, and for smaller, less developed industries. When the response cutoff is moved further out, results tend to suggest these factors predict slightly larger variation.

Table 3.5: *Average Response of Excess Industry Stock Returns to Industry News Across Country Borders, by Horizon and Time Period*

Results are based on estimated response coefficients (b) from regression Equation 3.6: $r^{ex}_{c1}(i)_{t:t+\tau} = b(i, c1, c2, y, \tau) z_{c2}(i)_{t^*} + \varepsilon(i, c1, c2, \tau)_t$. Standard errors for the ratio of delayed to total response are computed by applying the delta method to a covariance matrix derived using simultaneous estimation of initial and delayed responses with heteroskedastic-robust clustering on responding and origination countries, industry, and year $(c1, c2, i, y)$.

		Initial	Delayed	Total	Delayed/Total	
Years	Observations	$(\tau = 1)$	(Total minus Initial)	$(\tau = 30)$	Ratio	SE
1986-1994	34,239	0.013	0.041	0.054	0.76	0.14
1995-2002	88,994	0.030	0.039	0.069	0.56	0.10
2003-2010	116,899	0.030	0.019	0.049	0.38	0.08

finding of underreaction to industry news from other countries should come as no surprise. Could it be the case that the inefficiency found is unrelated to borders and is merely the result of a more general gradual diffusion of information between stock prices regardless of where the companies are located and traded? I address this concern in an analysis described in Appendix C.4; a simulation where industry portfolios in each country are split into two separate portfolios. I find that the response speed to industry news generated within the same country's stock markets is generally much more rapid than the response speed to industry news generated in other countries. However, the two are significantly correlated across countries, which suggests there are some common drivers of both inefficiencies.

3.4.1 What Speeds up Diffusion Across Borders?

Significant differences may exist between pairs of portfolios in the both the size and speed of responses to industry news that flows across country borders. In the remainder of this section, I investigate how these cross-sectional differences in the speed of response relate to the relevance of the industry news in foreign markets, features of the pairs of portfolios that facilitate information flow across borders (information links), and the ability of arbitrageurs to moderate short-run mispricing.

In addition to news from larger industry constituents, news has greater impact on prices across borders where fundamental ties are stronger. This is seen in Figure 3.4. For example, industry news is more informative about consumer demand when it comes from a country that imports a large fraction the industry output from a given country.[14] I obtain estimates of industry trade between country pairs in each year through a combination of databases from the UN and IMF. The correlation in the industry component of return on equity provides another measure of where news flow has greater impact. When this correlation is high, it is more likely that companies face similar risks across portfolios. I estimate these correlations by regression using Compustat Global data.

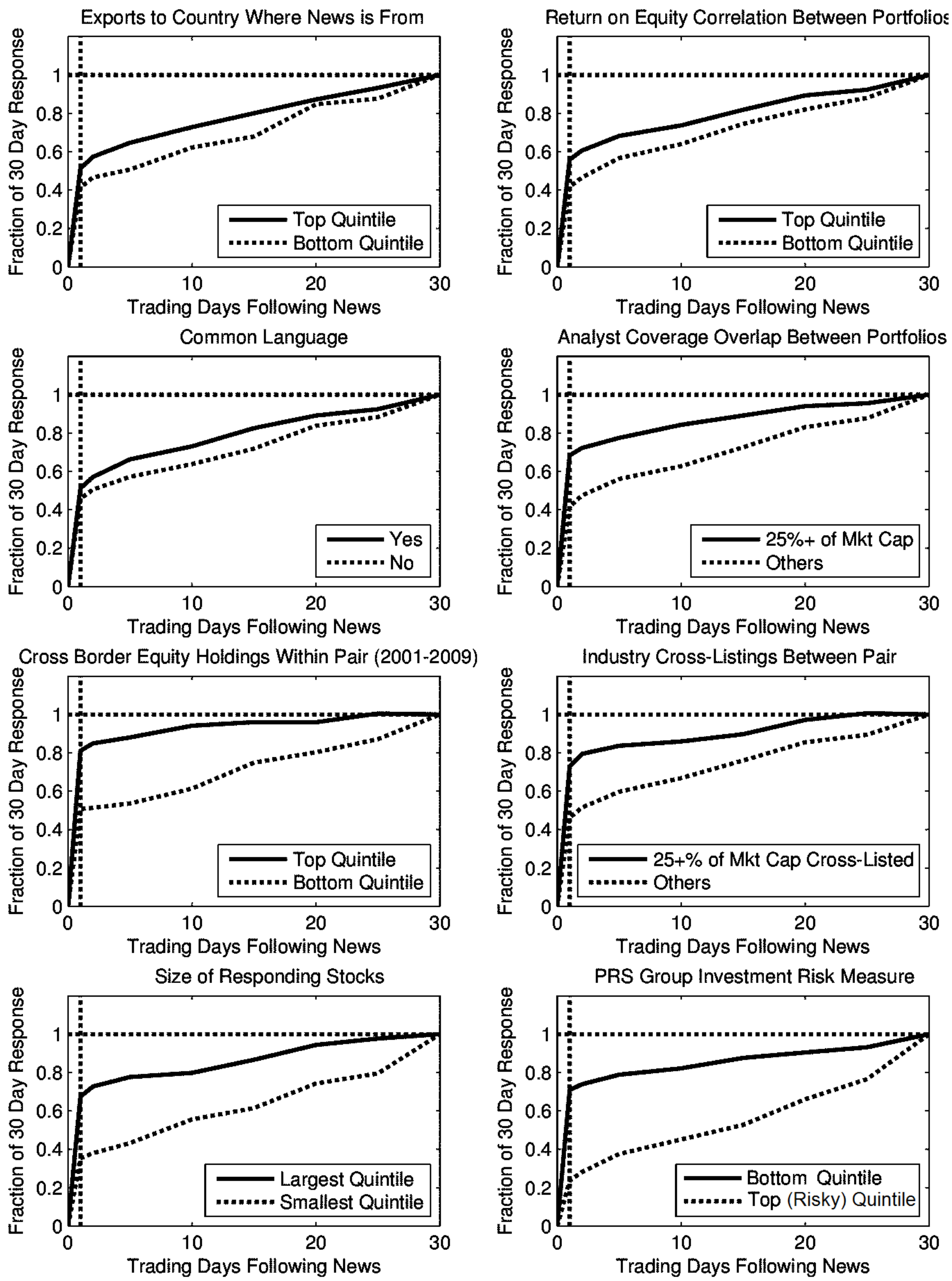
While the strength of fundamental ties should primarily predict the magnitude of the response of excess industry stock returns, there may also be some implications for the speed of the response. If investors are rationally inattentive, it may be that they choose to receive more information about and pay more attention to the most relevant foreign signals, namely where fundamental links are stronger. However, the top two panels of Figure 3.6 show only weak evidence in favor of a rational attention based explanation for variation in response speed. Similarly, Table 3.6 shows that while the largest quintile of portfolios generate news with more than three times the impact of the smallest quintile (30-day response coefficients of 0.104 and 0.031), the fraction of those responses that occur in the first day are comparable.

Another set of variables describe features of the information environment between portfolios that facilitate flow of industry news across borders. These include common analyst coverage across portfolios, cross-border equity holdings within the given pair of countries, and cross-listings between portfolios. I also consider the possibility that language barriers slow information flow.

The opinions of sell-side equity analysts play a role in cross-sectional pricing, so the overlap of equity analyst coverage across markets provides another channel for industry

[14]Rizova (2010) (also Albuquerque, Ramadorai, and Watagula (2011)) use trade as a link between stock market fundamentals.

Figure 3.6: *Average Response of Excess Industry Stock Returns to Industry News Across Country Borders*



Results are based on estimated response coefficients b from regression Equation 3.6: $r^{ex}_{c1}(i)_{t:t+\tau} = b(i, c1, c2, y, \tau) z_{c2}(i)_{t^*} + \varepsilon(i, c1, c2, \tau)_t$. Regressions are run over time horizons extending from day t out to 30 trading days following the news ($\tau = 1$ to 30), where t^* is the most recent trading day in $c2$ which closes prior to the end of day t trading in $c1$. In the plots above, coefficients are scaled to set the 30-Day response equal to one and are averaged across groups sorted by attributes of the portfolio where the news is from and the pair of portfolios between which the news is spreading.

Table 3.6: *Average Response of Excess Industry Stock Returns to Industry News Across Country Borders, by Horizon and Attributes of Country-Pairs and Portfolios*

The attributes used in the table are detailed in Appendix C.2. Results are based on estimated response coefficients (b) from regression Equation 3.6: $r^{ex}_{c1}(i)_{t:t+\tau} = b(i, c1, c2, y, \tau) z_{c2}(i)_{t^*} + \varepsilon(i, c1, c2)_t$. Day t^* is the most recent trading day in $c2$ which closes prior to the end of day t trading in $c1$. Standard errors are computed by applying the delta method to a covariance matrix derived using simultaneous estimation of initial and drift responses with heteroscedastic-robust clustering on responding and source countries, industry, and year. These standard errors are used to compute the two-sided p-values given above.

		Magnitude of Response			Response Efficiency			
	Observations	Initial	Delayed (t+2:t+30)	30 Day	Delayed/30 Day	SE	Difference	p-value
Size of Portfolio where Industry News is From								
Top Quintile	48,039	0.050	0.055	0.104	0.52	0.11	0.00	0.98
Bottom Quintile	48,003	0.015	0.016	0.031	0.53	0.08		
Attributes Related to Fundamental Ties between Industry Portfolios								
Exports to Country where Industry News is From								
Top Quintile	48,027	0.050	0.048	0.098	0.49	0.08	-0.10	0.20
Bottom Quintile	48,010	0.012	0.017	0.029	0.59	0.10		
Return on Equity Correlations Between Portfolios								
Top Quintile	48,026	0.043	0.034	0.077	0.44	0.09	-0.14	0.07
Bottom Quintile	48,025	0.017	0.023	0.040	0.58	0.08		
Attributes of the Portfolio Responding to the News Related to Arbitrage Costs								
Size of Stocks in the Responding Portfolio								
Top Quintile	48,035	0.048	0.023	0.071	0.33	0.08	-0.32	0.00
Bottom Quintile	48,025	0.019	0.034	0.053	0.65	0.08		
Volatility of Responding Portfolio Returns								
Bottom Quintile	47,902	0.024	0.019	0.043	0.45	0.09	-0.16	0.05
Top Quintile	47,920	0.027	0.041	0.068	0.61	0.10		
PRS Group Investment Risk Measure								
Bottom Quintile	46,485	0.043	0.018	0.061	0.29	0.08	-0.47	0.00
Top Quintile	53,610	0.014	0.044	0.058	0.76	0.05		

Continued on next page.

Table 3.6: *(Continued) Average Response of Excess Industry Stock Returns to Industry News Across Country Borders, by Horizon and Attributes of Country-Pairs and Portfolios*

		Magnitude of Response			Response Efficiency			
	Observations	Initial	Delayed (t+2:t+30)	30 Day	Delayed/30 Day	SE	Difference	p-value
Attributes Related to Information Links between Industry Portfolios								
Common Language within Country Pair								
Yes	93,873	0.037	0.035	0.072	0.49	0.07	-0.05	0.11
No	146,259	0.021	0.025	0.047	0.54	0.08		
Analyst Coverage Overlap Between Portfolios (1990-2010)								
>25+% Capitalization	34,353	0.072	0.033	0.105	0.32	0.07	-0.27	0.00
Others	198,215	0.020	0.028	0.049	0.58	0.08		
Cross-Border Equity Holdings within Pair (2001-2009)								
Top Quintile	26,002	0.066	0.015	0.082	0.19	0.08	-0.30	0.01
Bottom Quintile	25,972	0.016	0.015	0.031	0.49	0.11		
Industry Cross-Listings Between Pair								
>25+% Capitalization	9,209	0.088	0.033	0.121	0.27	0.06	-0.27	0.00
Others	230,923	0.025	0.029	0.054	0.54	0.07		

relevant information to travel across markets.[15] When portfolios are covered by analysts that also research stocks in a foreign country, the professional opinion reflected in stock prices should be better informed by news from both countries. Cross-border industry responses to industry news should then be more efficient. I measure the overlap in analyst coverage as the share of market capitalization in the industry portfolio of the responding country that has coverage by an equity analyst in IBES who also covers stocks primarily traded in the country where the news is from.

The amount of interest investors in one country have in news from another country's equity markets should relate to the amount that is invested in that equity market. Alternatively, viewing cross-border holdings as endogenous, if investors are viewed as endowed with certain attention or information regarding another country, this endowment might be directly reflected in the amount of equity holdings they choose to have. Either way, cross-border information flow should be greater and incorporation of cross-border news more rapid across borders between countries where investors in each country own substantial equity in the other country.[16] To measure holdings overlap, I use data from the IMF's Coordinated Portfolio Investment Survey to produce a measure of holdings for each country pair. The measure is scaled by GDP in each country so that it would be equal across country pairs if all countries were equally well capitalized and held identically composed foreign equity portfolios. The resulting measure is scaled to a standard deviation of one.

Cross-listings should facilitate transfer of news across borders. Suppose a company has a secondary stock listing in the foreign market where industry news originates.[17] The industry news should be incorporated relatively rapidly into the price of the secondary listing, as this news does not need to travel across borders. Arbitrageurs then ensure that

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[15] Other papers that relate the speed of information diffusion to analyst coverage include Hong, Lim, and Stein 2000 and Menzly and Ozbas 2010. However, note that I measure common analyst coverage, not just the level of analyst coverage in the country responding to the news.

[16] Cohen and Frazzini 2008 use common holdings as a proxy for attention paid to customer-supplier relationships, and find a positive relationship between common holdings and efficiency.

[17] Eun and Sabherwal 2003 and Gagnon and Karolyi 2010 provide evidence that price discovery for cross-listed securities takes place in both markets where the shares are listed.

prices between domestic and foreign listed stocks stay quite close. Through this process, industry news is transferred across borders into the price of the primary listing. The primary listing serves as a benchmark (or anchor) for the returns to other local industry stocks that are not cross-listed, so the foreign industry news may be incorporated more rapidly in their prices as well. A similar scenario plays out when the news originates in the market where the stock has its primary listing. To measure the intensity of cross-listings for each pair of portfolios, I compute the fraction of the market capitalization of each portfolio that is cross-listed in the other country of the pair, and combine these two values into the measure I use. Note that cross-listed companies are included in only in a single portfolio in my data. The mere fact that a company is cross-listed in two markets does not mechanically increase the return correlation of the two portfolios.

The middle plots of Figure 3.6 and second page of Table 3.6 show that responses between country pairs are much more rapid where there is substantial overlap in analyst coverage, large cross-border equity holdings within the pair, and substantial cross-listings within the pair. The delayed part of the response to industry news (day $t+2$ through $t+30$) is less than half as large for industry pairs with the strongest information linkages as it is for the average industry pair. Table 3.6 shows that each of these measures is also related to much larger total response sizes between country industry pairs.[18] However, it seems unlikely that rational allocation attention could alone account for the extreme differences in response speed found here given the apparently limited effect of the strength of fundamental ties on response speed.

Information may not flow as smoothly between countries that do not share a common language. Foreign investors who are unfamiliar with the language predominantly used by the media and/or businesses in a country may find themselves at at informational disadvantage, and are thereby discouraged from actively investing. Similarly, many local investors might find it too costly to pay attention to news coming from a country where

[18]International coverage by equity analysts and cross-listings are more common in industries that are more global in their operations. Analyst coverage, cross-border equity holdings, and cross-listings all occur more frequently across pairs of countries that are similar.

much of the information is in a foreign language. To gauge the impact of language as a barrier, I produce a dummy variable equal to one whenever a significant fraction of the population in the responding country understands at least one of the primary languages in the country where the signal originates.

Figure 3.6 and Table 3.6 show only modest evidence (p-value of 0.11) in favor of a language barrier affecting the response speed to cross-border industry news. This finding might relate to the dominance of the English language in the professional investing community across most of the world; my measures of language understanding are based on the fluency of the general population in each country. Measures of cultural distance (from the World Values Survey) between country pairs yield similarly weak results for their impact on response speed.

The third set of variables relate primarily to the costs facing arbitrageurs who might wish to act upon and correct the mispricing. The size of the stocks in the responding industry portfolio is a clear candidate. Price impact in the smallest stocks would significantly reduce the profitability of trading. I measure portfolio size as the log value-weighted average market capitalization of stocks in the portfolio. The result is scaled to a standard deviation of one. The volatility of the industry returns in the portfolio responding to the news is a cost to be borne by arbitrageurs as well. I measure this volatility as one-year moving average realized volatility. Finally, institutional risks discourage arbitrageurs from operating in some countries. As a proxy for the these risks to investment, such as expropriations or taxation and limits on repatriations and investments, I use the Investment Profile index produced by the PRS Group, multiply it by negative one (so it relates positively to the level of risk) and scale the index to a standard deviation of one.[19]

Figure 3.6 and Table 3.6 show that differences in the size of the stocks responding to the cross-border industry news and the institutional investment risks faced by arbitrageurs in different countries are associated with drastic differences in the speed of cross-border

[19] Erb, Harvey, and Viskanta 1996 relate PRS Group indices to priced country specific risk. Carrieri, Chaieb, and Errunza 2010 have used the Political Risk series as a proxy for implicit barriers to international investment.

news incorporation. The lowest risk quintile of portfolios under the PRS Investment Profile measure incorporate more than three-quarters of the impact of foreign industry news in the first day whereas the most risky incorporate only 29 percent by that time. These differences are even larger (though less precisely estimated) if responses are measured out through day $t + 60$.

3.4.2 Multivariate Model

While several of the proposed explanations meet with success in finding differences in the speed of information flow between markets, relationships between the explanatory variables (see correlations in Table 3.1) could confound conclusions drawn from the univariate analysis. To address this, I fit a multivariate model of responses to industry news from other countries. This model is used to assess explanations for cross-sectional variation in diffusion speed of industry news across borders.

The analyses so far have used direct estimates of response coefficients b from Equation 3.6. For the multivariate model, b is replaced by θX as in Equation 3.7 below, where X is the usual set of variables representing properties of links between portfolios. Also, Equation 3.7 includes news from all foreign countries on the right hand side of the regression, though this is unimportant since the industry news is orthogonal across countries by construction.

$$r^{ex}_{c1}(i)_{t:t+\tau} = \sum_{c \neq c1} \theta(\tau) X(i, c1, c, t) z_c(i)_{t^*} + \varepsilon(i, c1)_t \tag{3.7}$$

The coefficients θ describe how the variables X relates to the way excess industry stock returns respond to industry news. For example, $\theta(30)$ is large if X predicts larger total (30-day) responses to industry news, and $\theta(1)$ is large if X predicts larger initial responses to industry news. If X increases the drift following cross-border industry news then $\theta(30) > \theta(1)$.

Equation 3.7 is estimated in yearly cross-sections for initial ($\tau = 1$) and total 30-day ($\tau = 30$) responses to industry news. This means that coefficients are identified from cross-sectional and not time-series, variation in the explanatory variables. Some variables are not available for the entire data series spanning 1986 through 2010, so these are included in the cross-sectional regressions when available.[20]

Table 3.7 provides estimates of θ for initial, total, and delayed responses of excess industry stock returns to industry news. Initial responses are measured from the first day news can be responded to through the end of the following trading day ($\tau = 1$). Delayed responses accumulate thereafter through $t + 30$. The coefficients reported in Table 3.7 are the average of the available yearly cross-sectional estimates of θ. Standard errors are estimated under the assumption that errors are independent across years. This usual Fama MacBeth assumption appears approximately true in this application.

Table 3.7 does not provide a direct measure of the impact of the X on response speed. It does present the impact of X on the total magnitude of delayed response of stock returns (i.e. drift). An arbitrageur may find the absolute rather than relative size of drift to be more interesting; a relatively small underreaction to major news is more useful to know about than news of minor importance that is almost completely ignored. Table 3.7 shows that the largest drift is found in small developing countries (i.e. high investment risk) in response to news from major markets with strong fundamental ties to the responding market. For example, drift increases by about 41 percent (equals 1.20/2.93) for a one standard deviation increase in the size of the portfolio the news is from, and increases 26 percent for each one standard deviation increase in the responding country's investment risk as determined by the PRS Investment Profile index.

In order to assess the marginal impact of each variable X on the response speed of stock prices to cross-border news, a few more equations are required. Given Equation 3.7, the predicted ratio of delayed to total 30-day response of industry i stock returns in country $c1$ to industry news from country $c2$, $DELAY$, is given by Equation 3.8 below.

$$DELAY(i, c1, c2, t) = (\theta(30) - \theta(1))X(i, c1, c2, t)/\theta(30)X(i, c1, c2, t) \tag{3.8}$$

[20]These variables are analyst coverage overlap (1990-2010), cross-border equity holdings (2001-2009), and portfolio turnover (1995-2010).

Table 3.7: *Explanations for Variation in the Speed and Size of the Response of Excess Industry Stock Returns to Industry News from Other Countries*

The coefficients below are the θ from regression Equation 3.7: $r^{ex}_{c1}(i)_{t:t+\tau} = \sum_{c \neq c1} \theta(\tau) X(i, c1, c, t) z_c(i)_{t^*} + \varepsilon(i, c1)_t$. X denotes the set of variables used to explain the magnitude or speed of country $c1$ industry i responses to day t news z_t from country c. Controls included in X but not detailed in the table below include a constant term, monthly turnover of the portfolio responding to the industry news, a measure of cultural distance, a measure of overlap in stock market trading hours, and dummy variables for adjacent country pairs. The coefficients in this table reflect the average across years of regression coefficients that are estimated separately in yearly cross-sectional regressions. Day t^* is the most recent trading day in $c2$ which ends before the close of day t trading in $c1$. Standard errors in ( ) are estimated under the assumption of independence of residuals across years, allowing for arbitrary residual correlations within each year. Bold type indicates coefficients that are significant at a five percent level and italics indicate coefficients significant at a ten percent level.

		Impact on Response (x 100)		
Variable X	$\sigma(X)$	Initial: $\theta(1)$	30 Day: $\theta(30)$	Delayed: $\theta(30) - \theta(1)$
Full Sample Mean		**2.75**	**5.68**	**2.93**
Attributes of Portfolio Where the Industry News is From ($pf(c)$)				
Size of $pf(c)$	1.00	**1.12**	**2.33**	**1.20**
		(0.10)	(0.21)	(0.16)
Log($\sigma(z(i,c))$)	0.45	**-0.34**	**-1.77**	**-1.42**
		(0.15)	(0.56)	(0.55)
Attributes Related to Fundamental Ties between Industry Portfolios				
Exports from $c1$ to c	1.00	*0.18*	**0.70**	**0.52**
		(0.09)	(0.21)	(0.18)
ρ(Return on Equity)	1.00	**0.47**	**0.82**	*0.35*
		(0.09)	(0.25)	(0.20)
Attributes of the Portfolio Responding to the News ($pf(c1)$) Related to Arbitrage Costs				
Size of Stocks in $pf(c1)$	1.00	**0.35**	0.04	-0.31
		(0.13)	(0.35)	(0.29)
Log($\sigma(R^{ex}(i, c1))$)	0.52	**0.35**	**0.86**	0.50
		(0.12)	(0.41)	(0.37)
Investment Risk	1.00	-0.11	0.66	0.77
		(0.11)	(0.57)	(0.54)

Continued on next page.

Table 3.7: *(Continued) Explanations for Variation in the Speed and Size of the Response of Excess Industry Stock Returns to Industry News from Other Countries*

		Impact on Response (x 100)		
Variable X	$\sigma(X)$	Initial: $\theta(1)$	30 Day: $\theta(30)$	Delayed: $\theta(30) - \theta(1)$
Attributes Related to Information Links between Industry Portfolios				
Common Language	0.49	**0.57**	**1.13**	0.56
		(0.15)	(0.52)	(0.47)
Analyst Coverage Overlap				
Between Portfolios	0.22	**5.08**	**6.18**	1.10
(1990-2010)		(0.65)	(1.76)	(1.64)
Cross-Border Equity				
Holdings Within Pair	1.00	0.10	-0.24	**-0.35**
(2001-2009)		(0.11)	(0.19)	(0.17)
Industry Cross-Listings	0.09	**6.92**	**4.81**	-2.11
Between Pair		(0.76)	(1.56)	(1.43)

I denote the impact of X_j (the j-th explanatory variable in X) on response delay as $\Delta DELAY_j$. This $\Delta DELAY_j$ is the derivative of $DELAY$ with respect to X_j evaluated at the sample average across all portfolio pairs and years, $\overline{DELAY}$. This measure, given by Equation 3.9, is scaled by the cross-sectional standard deviation of X_j. That way it can be interpreted as the estimated change in the delayed part of the response (to cross-border industry news) given a one-standard deviation increase in X_j from the mean.

$$\Delta DELAY_j = \sigma(X_j) \times \overline{DELAY} \times \left(\frac{\theta_j(30) - \theta_j(1)}{(\theta(30) - \theta(1))\bar{X}} - \frac{\theta_j(30)}{\theta(30)\bar{X}}\right) \tag{3.9}$$

Table 3.8 provides estimates of $\Delta DELAY$ using the same set of explanatory variables X as in Table 3.7, as well as estimates based on variations of this baseline specification as a robustness check. Results show the importance of information links such as common analyst coverage and cross-listings in generating spread in response speed. A one standard deviation (i.e. 22 percent) increase in the fraction of portfolio capitalization covered by analysts that provide coverage of both countries in the pair is associated with a decrease of about 0.08 in the ratio of delayed to total response to industry news. This is equivalent to a roughly 15 percent decrease in the size of the average drift. A one standard deviation (i.e. nine percent) increase in the fraction of the portfolio capitalization cross-listed in both countries in the pair predicts a similar size decrease in the drift.

In contrast to the univariate plots, there is no evidence that strong fundamental ties lead to more rapid responses to industry news from other countries. Earlier results (e.g. Figure 3.6) finding a modest relationship between fundamental ties and response speed were driven by the generally positive correlations between fundamental ties and information links (see Table 3.1).

Arbitrage costs remain important. Each standard deviation increase in the average size of the responding stocks decreases the delayed to total response ratio by about 0.06, reducing the drift by over 10 percent. The PRS investment risk measure has a very large but imprecisely estimated impact on response speed, with greater risks facing foreign investors associated with slower responses. The lack of precision relates to the fact that this risk measure is a country level variable, and does not exploit variation across industries or different pairs of countries. Coefficient estimates are similar, but a bit more precisely estimated when they are taken as a precision instead of equal weighted averages across years; coefficient estimates θ from earlier years are significantly less precise.

Some stock markets are much larger, considered less risky, and are more connected with other markets via analyst coverage or cross-listing. As a result, Equation 3.7 estimates a large spread across countries in the ratio of delayed to 30-day responses to cross-border industry news. This spread in estimates is illustrated in Table 3.9. Cross-border industry news is incorporated into prices most rapidly in larger developed markets with ample international analyst coverage and cross-listings (US, UK, France, Germany, Finland) and least rapidly in small relatively isolated emerging markets (Sri Lanka, Pakistan, Argentina, Turkey, Thailand). Table 3.9 also provides estimates of the delayed-total response from the direct (non-parameterized) regressions on industry news from Equation 3.6. The two sets of estimates are highly correlated; the variables used in X fit a great deal of the variation in average response speed across countries.

These conclusions about the drivers of variation in response speed are robust to exclusion

Table 3.8: *Estimates of $\Delta DELAY$: Baseline Specification from Table 3.7 and Variations*

$\Delta DELAY$ is the estimated impact on the delayed to total response ratio (of excess industry stock returns to industry news from other countries) due to a one standard deviation increase in X. This is computed in each year as the derivative of the estimated ratio of delayed (days $t+2$ through $t+30$) to total 30-day excess industry stock return response evaluated at mean delayed and 30-day responses. Variables X are scaled so that the derivative corresponds to the estimated change per one standard deviation increase in X. Estimates of responses to industry news are given by regression Equation 3.7: $r^{ex}_{c1}(i)_{t:t+\tau} = \sum_{c \neq c1} \theta(\tau) X(i, c1, c, t) z_c(i)_{t^*} + \varepsilon(i, c1)_t$. The specification in column [A] is the baseline model from Table 3.7. The dependent variable (stock returns) in column [B] is winsorized at the 1st and 99th percentiles. Column [C] is the same as the baseline model except without the additional controls from [A] that are omitted from Table 3.7 and below. Columns [D] through [G] provide results under a variety of fixed effects with all controls from the baseline model [A] included except for those that are not identified under the indicated fixed effects. Standard errors in ( ) are estimated under the assumption of independence of residuals across years, allowing for arbitrary residual correlations within each year. Bold type indicates coefficients that are significant at a five percent level and italics indicate coefficients significant at a ten percent level.

				Fixed Effects			
Variable X	Baseline	Winsorized	No Addtl Controls	Country $c1$	Industry i	$c1$ X i	$c1$ X c
	[A]	[B]	[C]	[D]	[E]	[F]	[G]
Attributes of Portfolio Where the Industry News is From ($pf(c)$)							
Size of $pf(c)$	0.001	-0.001	-0.003	-0.006	**0.036**	0.029	0.032
	(0.015)	(0.011)	(0.0015)	(0.017)	(0.017)	(0.020)	(0.024)
Log($\sigma(z(i,c))$)	-0.041	-0.034	-0.040	-0.036	-0.024	*-0.048*	-0.040
	(0.025)	(0.021)	(0.025)	(0.025)	(0.026)	(0.024)	(0.026)
Attributes Related to Fundamental Ties between Industry Portfolios							
Exports from $c1$ to c	0.027	0.017	*0.026*	0.036	0.001	0.003	0.037
	(0.016)	(0.015)	(0.015)	(0.024)	(0.016)	(0.023)	(0.025)
ρ(Return on Equity)	-0.013	-0.012	-0.017	-0.001	-0.033	-0.003	-0.011
	(0.016)	(0.016)	(0.016)	(0.020)	(0.026)	(0.022)	(0.023)

Continued on next page.

Table 3.8: *(Continued) Estimates of $\Delta DELAY$: Baseline Specification from Table 3.7 and Variations*

				Fixed Effects			
Variable X	Baseline	Winsorized	No Addtl Controls	Country $c1$	Industry i	$c1$ X i	$c1$ X c
	[A]	[B]	[C]	[D]	[E]	[F]	[G]
Attributes Related to Information Links between Industry Portfolios							
Common Language	-0.002	0.004	0.005	0.005	-0.002	0.007	
	(0.020)	(0.018)	(0.021)	(0.027)	(0.019)	(0.027)	
Analyst Coverage Overlap	**-0.081**	**-0.082**	**-0.073**	**-0.071**	**-0.080**	*-0.063*	**-0.082**
	(0.033)	(0.030)	(0.034)	(0.031)	(0.032)	(0.032)	(0.033)
XBorder Equity Holdings	-0.039	-0.024	-0.041	-0.020	-0.041	-0.016	
	(0.031)	(0.029)	(0.031)	(0.031)	(0.028)	(0.029)	
Cross-Listings	**-0.073**	**-0.066**	**-0.075**	**-0.068**	**-0.061**	**-0.039**	**-0.056**
	(0.013)	(0.012)	(0.014)	(0.013)	(0.014)	(0.013)	(0.012)
Attributes of the Portfolio Responding to the News ($pf(c1)$) Related to Arbitrage Costs							
Size of Stocks in $pf(c1)$	**-0.059**	**-0.052**	**-0.058**	**-0.066**	-0.040		*-0.065*
	(0.025)	(0.020)	(0.025)	(0.032)	(0.025)		(0.033)
Log($\sigma(R^{ex}(i, c1))$)	0.006	0.003	0.009	-0.012	0.014		-0.016
	(0.016)	(0.012)	(0.016)	(0.020)	(0.018)		(0.020)
Investment Risk	0.075	0.062	0.072		0.098		
	(0.053)	(0.040)	(0.051)		(0.059)		

Table 3.9: *Delay in Response to Cross-Border Industry News, by Country Responding to the News*

The delay in response is computed as the ratio of the average delayed (day $t+2$ through $t+30$) response to the 30-day (day t through $t+30$) response, with each observation weighted by the industry's share of the given country's capitalization in the year. Responses are the estimated coefficients on industry news from regression Equations 3.6: $r^{ex}_{c1}(i)_{t:t+\tau} = b(i, c1, c2, y, \tau) z_{c2}(i)_{t^*} + \varepsilon(i, c1, c2)_t$ and 3.7: $r^{ex}_{c1}(i)_{t:t+\tau} = \sum_{c \neq c1} \theta(\tau) X(i, c1, c, t) z_c(i)_{t^*} + \varepsilon(i, c1)_t$.

Country	From Equation 3.7 Based on θX	From Equation 3.6 Based on b
Ten Largest Markets in Dataset (as of Dec 2010)		
United States	0.19	0.04
Japan	0.36	0.44
China	0.57	0.63
United Kingdom	0.30	0.41
France	0.32	0.41
India	0.59	0.72
Germany	0.33	0.46
Australia	0.31	0.38
Switzerland	0.34	0.48
Five Most Efficient Markets in Dataset as Predicted by Equation 3.7		
United States	0.19	0.04
United Kingdom	0.30	0.41
France	0.32	0.41
Germany	0.33	0.46
Finland	0.33	0.40
Five Least Efficient Markets in Dataset as Predicted by Equation 3.7		
Thailand	0.67	0.52
Turkey	0.68	0.71
Argentina	0.70	0.78
Pakistan	0.70	0.84
Sri Lanka	0.80	1.11 [1]

[1] In regressions based on Equation 3.6, the average estimated initial response of Sri Lankan industry portfolios is slightly negative, which explains why this figure is greater than one.

of outliers, changes in controls, and various fixed effects represented by the results in columns [B] through [F] of Table 3.8. Column [B] shows that the same conclusions hold when the dependent variable (excess industry stock returns) are winsorized at the 1st and 99th percentiles. Column [C] drops the controls in the baseline specification that do not appear in the results tables. These dropped controls do not predict substantial variation in response speed and size, and their removal has minimal effect on conclusions about the remaining variables. Fixed effects implemented in columns [D] through [G] address the concern that conclusions may be driven by unobserved variables that are functions of a given country, portfolio, industry, or pair of countries. For example, portfolios with many large overlaps in analyst coverage with other portfolios might be those that receive more attention from professional investors in general. This attention is not directly measured and could generate unobserved variable bias, but is controlled for by imposing portfolio fixed effects in each year, which is done in column [F]. Not all variables continue to appear when fixed effects are applied; variables that vary only along the same dimensions as the fixed effects within each year cannot be identified.

However, it seems plausible that responses are more efficient where news is more important simply because investors may rationally pay more attention to more important sources of news and use more capital to correct mispricings resulting from underreaction to this news. Since expected total response varies over years, industries, and country pairs, it is not controlled for by the fixed effects in the robustness analysis represented in Table 3.8. In Appendix C.5, I consider the possibility that apparent increases in response speed due to equity analysts and cross-listings are significantly driven by a relationship with overall response size. In short, this appears unlikely given that several variables (e.g. size of the portfolio the industry news is from) that predict even more substantial increases in total response size have minimal impact on the speed of response. The impact of these other fundamental links on response speed should be significant if rational allocation of attention is a major driver of variation in response speed.

3.5 Changes in Responsiveness to Cross-Border Industry News over Time and Trading Strategy Profitability

Figure 3.7 plots the average coefficient b from yearly cross-sectional regressions of Equation 3.6. The total height of each bar reflects the average 30-day response of excess industry stock returns to industry news. This response is split into portions attributed to initial (black) and delayed (white) response. The magnitude of the 30-day response is fairly similar across years, with 1999 as a noticeable exception.[21] In 1999, stocks in technology related industries outperformed other industries substantially in many countries, but these gains typically spread across borders with a lag. While 30-day responses have been fairly consistent, initial responses have grown over time, corresponding to the increase in response speed noted in Figure 3.5. One possibility that Figure 3.7 suggests is that substantial and inefficient transmission of industry news in 1999 woke investors up to the importance of information contained in foreign industry returns. Prior to 1999 drift typically exceeded initial response while the reverse is true afterwards.

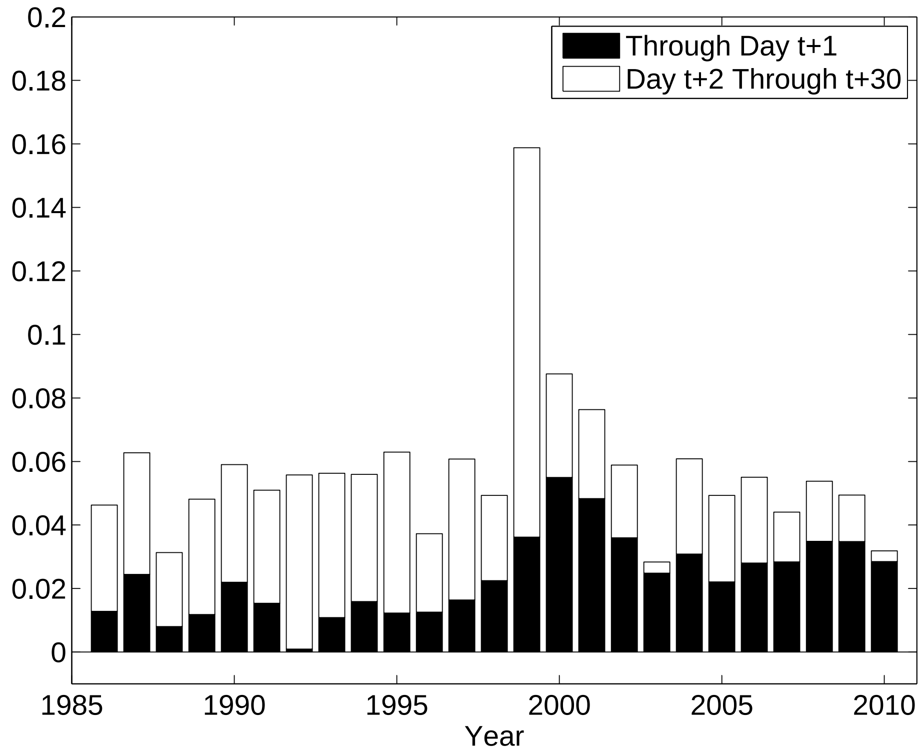
Improvement in response speed is predicted by some of the same variables that predict substantial cross-sectional variation in response speed. The top plot of Figure 3.8 shows the ratio of initial to total (30-day) response by year (along with a five year average) from Equation 3.6 against a yearly average of fitted values from Equation 3.7.[22] These fitted values are computed using the time-series mean of θ, so variation in the fitted time-series comes from changes over time in the means of the explanatory variables X.[23] About half of the trend in response speed is explained by this variation, with the remaining unexplained

[21] If the set of countries included in the figure were held constant over the years, a slight upwards trend in 30-day response would emerge. Countries for which data is added later in the time series tend to be smaller and produce industry news with less impact in other countries.

[22] Since a few of the variables X are unavailable for part of the time series, their values are imputed by linear regression using the remaining variables when necessary. The trends in fitted values in Figure 3.8 are affected very little by this imputation; results are similar when using time-series means for the missing variables instead of imputed values.

[23] The downtrend in efficiency seen in the early 1990s is mostly due to the incremental addition of small emerging markets to the dataset. Future drafts of this paper will control for country composition.

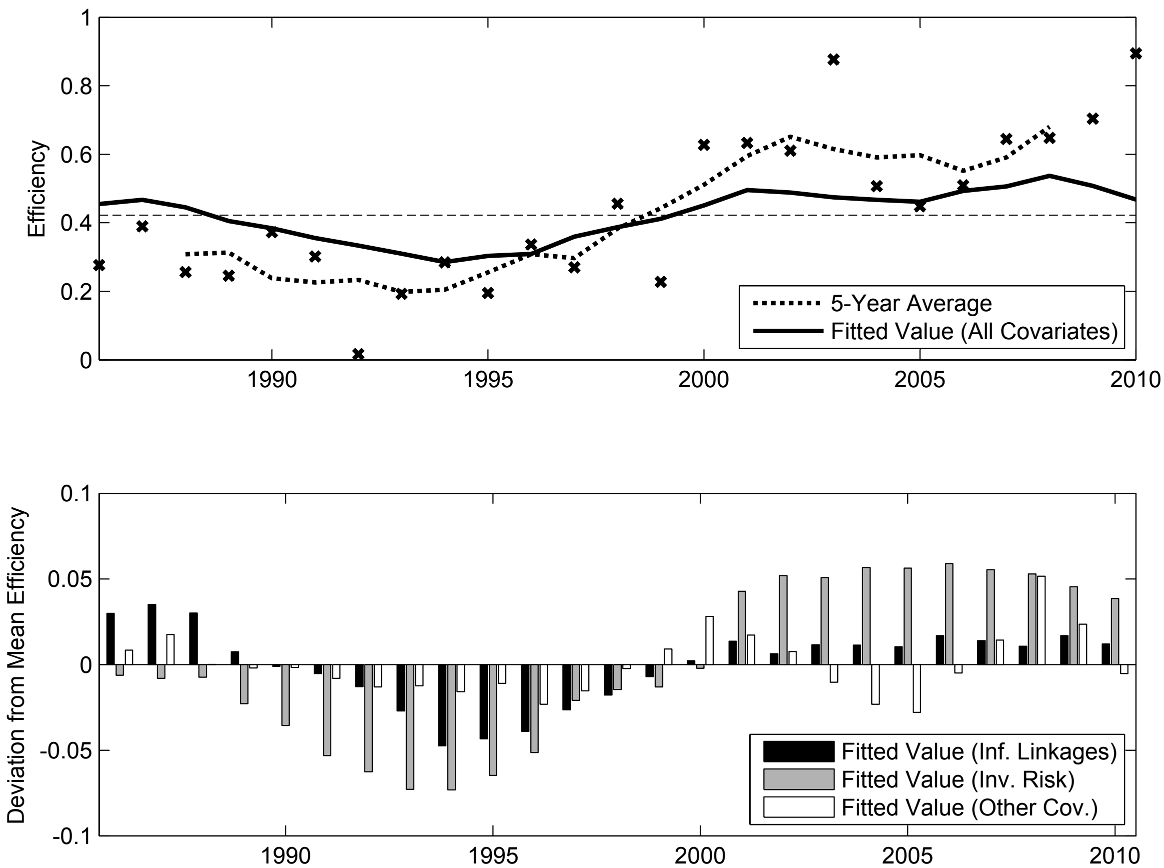
Figure 3.7: *Responses of Excess Industry Stock Returns to Industry News from Other Countries, Averages by Year*



Results are based on the average (across country pairs and industries) stock return response coefficients b estimated from yearly cross-sectional regressions of Equation 3.6: $r^{ex}_{c1}(i)_{t:t+\tau} = b(i, c1, c2, y, \tau) z_{c2}(i)_{t^*} + \varepsilon(i, c1, c2, \tau)_t$. The full bar comes from regressions of returns through day $t + 30$ ($\tau = 30$), while the solid black part of the bar uses returns through day $t + 1$.

half attributed to either imperfections in the model or investors learning over time.

Figure 3.8: *Trends in the Ratio of Initial to 30-Day Stock Price Responses (Efficiency) to Industry News from Other Countries*



Top Plot: The x represent estimates of efficiency based on average response coefficients b from Equation 3.6 across all country pairs and industries in the given year. The dashed line gives a five year average of these x. The solid black line represents estimates of efficiency based on fitted response coefficients from Equation 3.7 across all country pairs and industries in the given year. The coefficients θ predicting the impact of X on responses are held constant across years. Bottom Plot: Each bar represents the deviation of fitted values of efficiency from the time-series average attributed to variables in each of three categories: 1) investment safety (PRS Investment Profile), 2) information links (shared analyst coverage, common equity holdings within the country pair, and cross-listings), and 3) the remaining 13 variables in X.

The bottom panel of Figure 3.8 decomposes time-series deviations from response speed, the ratio of initial to 30-day response, into portions attributed to investment risk, information links, and all other variables. Investment risk (PRS Investment Profile) emerges as the single most important predictor of improving efficiency, but information links (overlap in analyst coverage, common equity holdings, and cross-listings) remain significant as well.

Figure 3.9 provides some justification for the notion that the same variables predict cross-sectional and time-series variation in response speed. For each country, I compute the changes in average common analyst coverage, cross-listings, and investment risk between the pre-1995 time period and the post-2002 time period.[24] I take the principal component of these three series, and sort countries by this principal component measure. Responses to cross-border industry news are plotted for countries that have shown the greatest improvement under this measure on the left hand side, and least improvement on the right hand side. Countries that have shown the greatest improvement under the principal component measure have shown the most gain in response speed, and vice versa.

3.5.1 Trading Strategy

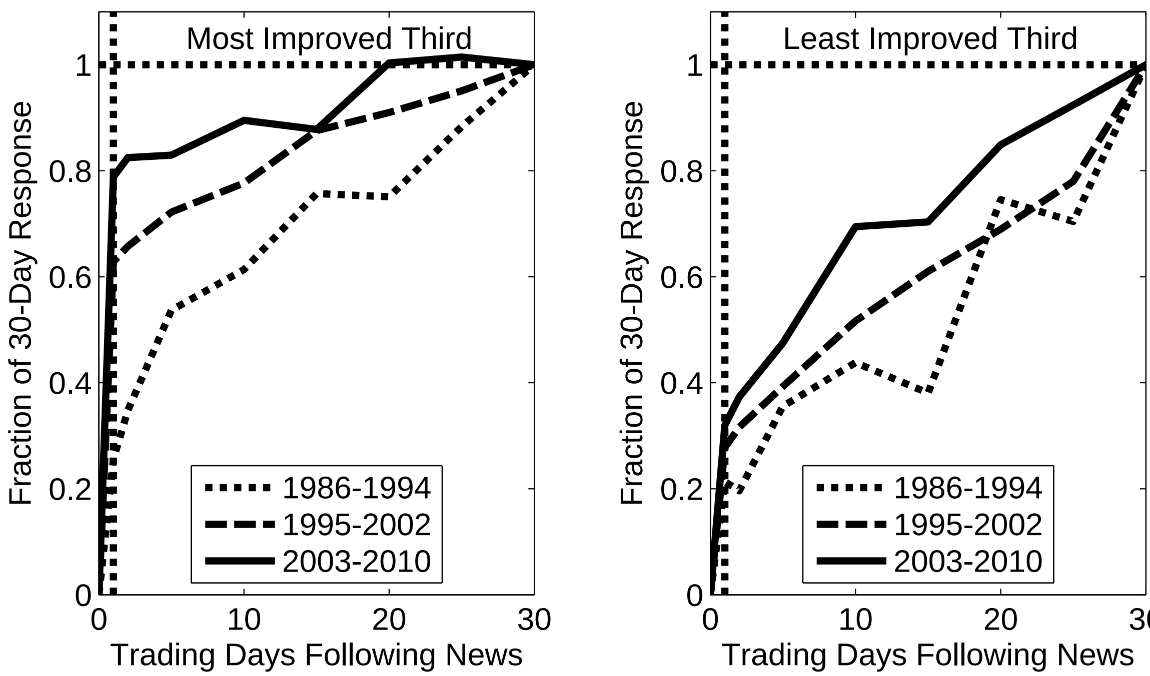
Interpreting the myriad foreign returns is a nontrivial task. Trading hours are generally asynchonous, and the extent to which returns reflect news that is relevant in other countries is almost never clear ex-ante. Rather than inducing a forward looking bias by relying on the multivariate model to identify portfolios pairs susceptible to large drift, I construct a simple cross-sectional trading strategy that buys industries that have just been exposed to good news (proxied here by high industry returns) in foreign markets, and vice versa.

The "global momentum"strategy constructed in this test buys industry portfolios in each country in proportion to the amount by which the industry has recently outperformed in foreign markets, and vice versa for sales. The performance of foreign industry portfolios is measured by comparing the cumulative industry return over days $t-1-N$ through $t-1$ (where N reflects the portfolio formation and holding period) with the cumulative industry weight adjusted return for that market over the corresponding period.[25] Excess industry returns are then aggregated across foreign markets using market capitalization of the industry in each country (from the past month) as weights.

[24]Only the 39 (out of 55) countries that are present in the data prior to 1995 are included in this analysis.

[25]As with earlier analysis, the use of industry weight adjusted market returns does not result in significantly different results from the use of value weighted market returns or characteristic benchmark returns, but is used as it is a more industry neutral measure of returns than value weighted returns in many smaller stock markets.

Figure 3.9: *Average Response of Excess Industry Stock Returns to Industry News from Other Countries, by Time Period and Changes in Analyst Coverage Overlap, Cross-Listings, and Investment Risk*



Responses to news are based on estimated response coefficients b from regression Equation 3.6. Regressions on day t industry news from other countries are run over time horizons extending from day t out to $t + 30$. The left plot is average b across all country pairs and industries where the country responding to the news is in the top third of countries in terms of increases in the principal component of analyst coverage overlap, cross-listings, and investment risk (PRS Investment Profile) between the 1986 to 1994 and 2003-2010 time periods. The right hand side plot similarly averages across groups where the country responding to the industry news ranks in the bottom third in terms of these efficiency related improvements.

Domestic industry portfolios are bought at the closing prices on day t, which allows the domestic market at least one full trading day to price the foreign news. Since most drift occurs within the first month, I focus on a monthly holding period ($N = 20$). The specific dates on which portfolios are formed are arbitrary, so the strategy invests $1/N$ in each of the N possible sets of formation dates.

Table 3.10 provides the mean monthly returns to global momentum (long $1, short $1) across each of three time periods.[26] Returns are given separately for strategies that set up equally sized long-short portfolios in each country as well as for strategies that set up long-short strategies in each country in proportion to the market capitalization of that country's stock markets. Smaller markets generally respond more slowly to cross-border industry news, so the strategy that invests equal (as opposed to value weighted) amounts in each market is a bit more profitable, with raw returns averaging 72 versus 63bp per month across the time series. Table 3.10 does not break out returns on the global momentum strategy separately by country, but the level of profitability in each country is significantly correlated with the estimated country-level ratio of delayed to 30-day responses (as in Table 3.9).[27]

Figure 3.10 plots cumulative returns to the global momentum trading strategy. With the exception of 1999, raw trading strategy returns are quite consistent. The large returns in 1999 correspond to large estimated drift for the year in Figure 3.7.

Despite being based on the same underlying mechanism (news travels slowly across borders) the time series of returns is quite distinctive from the returns on the international trade momentum strategy documented by Rizova (2010) and elaborated upon by the trade credit strategy of Albuquerque, Ramadorai, and Watagula (2011). In Rizova's strategy, most returns accumulate during the late 1980s and during the Asian Financial Crisis in 1997-1999. A key difference is that Rizova's strategy trades market portfolios across countries whereas

[26] As usual with a long-short strategy, the returns assume there is also $1 of non interest bearing capital held as collateral.

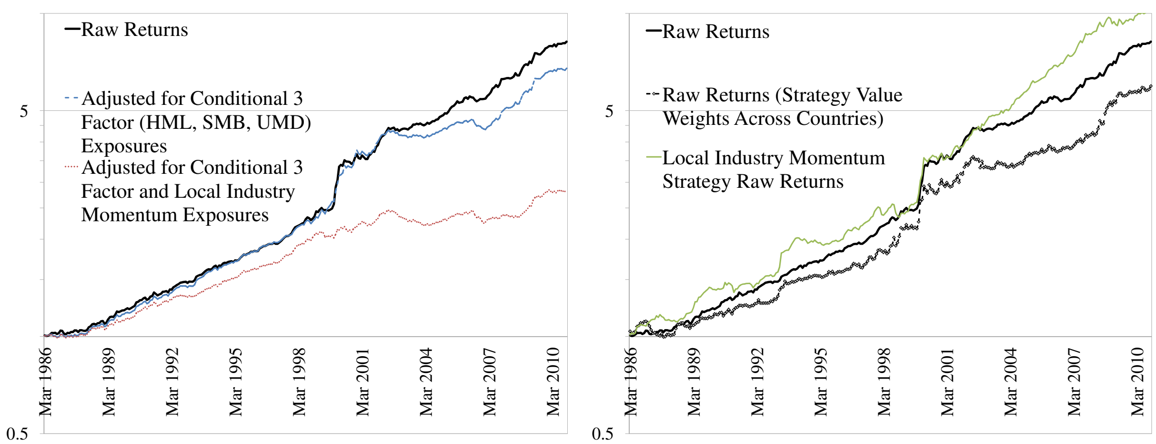
[27] The global momentum trading strategy is economically and statistically significantly profitable in all but few markets.

Table 3.10: *Global Industry Momentum Trading Strategy Monthly Returns, Alphas, and Sharpe Ratios*

The global industry momentum trading strategy buys stock in each country in industries whose stock portfolios have outperformed in other countries over the past month, and vice versa for sales. The local industry momentum portfolio is the trading strategy of Grinblatt and Moskowitz (1999) which buys stock portfolios in industries that have outperformed locally over the past month. Risk factor adjustments are carried out using twelve month rolling windows to estimate risk factor loadings. Risk factors are constructed by the method of Fama and French. Sharpe ratios are monthly. Bold type indicates coefficients that are significant at a five percent level and italics indicate coefficients significant at a ten percent level.

		Raw Returns	Three Factor Alpha SMB, HML, UMD	Three Factor Plus Local Industry Momentum
		Strategy Invests Equally Across Countries		
1986-1994	Returns	**0.51%**	**0.50%**	**0.39%**
	S.E.	(0.09%)	(0.09%)	(0.08%)
	Sharpe [2]	0.54	0.54	0.46
1995-2002	Returns	**0.99%**	**0.97%**	**0.48%**
	S.E.	(0.21%)	(0.18%)	(0.11%)
	Sharpe	0.48	0.55	0.44
2003-2010	Returns	**0.68%**	**0.51%**	*0.20%*
	S.E.	(0.12%)	(0.12%)	(0.10%)
	Sharpe	0.58	0.43	0.20
1986-2010	Returns	**0.72%**	**0.65%**	**0.36%**
	S.E.	(0.09%)	(0.08%)	(0.06%)
	Sharpe	0.49	0.49	0.37
		Strategy Invests Across Countries in Proportion to Their Capitalization		
1986-1994	Returns	**0.42%**	*0.23%*	*0.19%*
	S.E.	(0.14%)	(0.13%)	(0.11%)
	Sharpe	0.29	0.18	0.16
1995-2002	Returns	**0.85%**	**0.74%**	**0.69%**
	S.E.	(0.31%)	(0.27%)	(0.12%)
	Sharpe	0.28	0.28	0.59
2003-2010	Returns	**0.63%**	0.29%	*0.22%*
	S.E.	(0.18%)	(0.18%)	(0.11%)
	Sharpe	0.35	0.16	0.20
1986-2010	Returns	**0.63%**	**0.41%**	**0.36%**
	S.E.	(0.13%)	(0.12%)	(0.07%)
	Sharpe	0.29	0.21	0.31

Figure 3.10: *Cumulative Log Return to Trading Strategies, March 1986 through November 2010*



The global industry momentum trading strategy buys stock in each country in industries whose stock portfolios have outperformed in other countries over the past month, and vice versa for sales. The local industry momentum portfolio the trading strategy of Grinblatt and Moskowitz (1999) which buys stock portfolios in industries that have outperformed locally over the past month. On the left hand side plot, returns on a global industry momentum strategy that invests equal amounts in each market are compared to returns on the same strategy after an adjustment for Fama French market, size, and value risk factors, and after an additional adjustment for loadings on the local industry momentum strategy. On the right hand side plot, returns are shown for a global industry momentum strategy that invests equally across markets as well as for a strategy that invests across markets in proportion to their capitalization. Raw returns to the local industry momentum strategy are also shown on the right hand side plot.

the global industry momentum strategy trades industries within each country, with minimal exposure to market returns in any country. These strategies can be combined for significant improvement in Sharpe ratios over either strategy individually.

In addition to raw returns, I report trading strategy returns under two sets of risk adjustments (alphas). Risk factor loadings for each set of adjustments are computed using twelve-month rolling windows. The first set of reported alphas are based on adjustments for exposure to Fama-French risk factors (market, size, and value). The second adjustment controls for the similarity between the global industry momentum strategy and a monthly local industry momentum strategy as advocated by Moskowitz and Grinblatt (1999).[28] Monthly industry returns are correlated across countries, so an industry that outperforms in other countries is likely to outperform at home. As a result, the global and local industry momentum strategies often yield similar portfolios and have an average return correlation of 0.59.

Controlling for local industry momentum in addition to Fama-French factors significantly reduces the profitability of the global industry momentum trading strategy, especially in 1999. After both sets of adjustments are applied, the strategy's average monthly alpha declines to 36bp per month (either value or equal weighted positions across countries), but remains highly significant and has a low monthly standard deviation of just over one percent. However, local and global industry momentum have grown more similar in the past decade, reducing the incremental value of employing a global momentum trading strategy (as seen by the thick dashed line in the left hand plot of Figure 3.10). Since 2003, the global momentum trading strategy has yielded returns of only about 2.5 percent per year after controlling for local industry momentum and Fama French factors.

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[28]The most profitable local industry momentum strategy published by Moskowitz and Grinblatt was a strategy that forms portfolios monthly based on the past month's performance.

3.6 Conclusion

Industry returns bear relevant industry news for countries around the globe. This news is incorporated into stock prices at such a gradual rate that national borders appear to be a barrier to information flow. However, just as some market pairs appear segmented and others integrated with respect to risk prices, industry news spreads quickly between some pairs of industry portfolios and slowly between others. I use a multivariate model to disentangle explanations for this variation.

Overlap in equity analyst coverage and cross-listings between two industry stock portfolios are important links by which relevant industry news can be transmitted between portfolios. I show that drift relative to total response to industry news is reduced by about 0.08 for each one standard deviation increase in cross-listings or overlap in equity analyst coverage with the country where the news is from. In contrast I find limited connection between the strength of fundamental ties and response speed. For example, news from large industry portfolios or consumer markets has a much larger impact on stock prices in other countries, but this news appears in stock prices about as gradually as news from small portfolios or consumer markets. Of course, response speed is also related to the difficulty of arbitrage. Industry news is incorporated much more slowly in portfolios of small stocks and in developing markets.

Although responses to industry news across borders have historically been quite inefficient, responses have sped up drastically over the past 25 years. While drift used to account for the majority of cross-border responses, this fraction has halved, and many emerging markets today respond about as quickly as did developed markets 20 years ago. About half of this improvement relates to substantial reductions in institutional risk (such as expropriation) facing foreign investors in many of the countries and improvements in the extent of information links between portfolios in different countries such as shared analyst coverage and cross-listings. The other half of this improvement may reflect investor learning.

Trading on underreaction to foreign industry returns has been profitable historically, earning average excess returns of 8 to 9 percent a year over the past 25 years. However, as correlations in monthly industry returns have increased across countries, this strategy has become less distinct from a local industry momentum strategy. As a result, the profitability offered beyond local industry momentum has eroded to below three percent per year. If information links across markets continue to improve and investors continue to learn about the importance of signals from foreign markets, the processing and incorporation of information across markets into prices will continue to speed up and profitability of the trading strategies will decline further.

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Appendix A

Appendix to Chapter 1

A.1 PSID Data Screens

Household heads are considered "out of the labor force" if they indicate that they are a student, homemaker, permanently disabled, or retired. If labor status is unavailable for a given year, the worker is considered to be in the labor force only if they are classified as in the labor force in both surrounding years.

I change a worker's self-reported employment status from unemployed to employed in worker-years where the worker was employed for over 1,500 hours and this represents at least 80% of the worker's lagged average employment hours. This change affects about 10% of all self-reported unemployment years. I change the self-reported status for about as many worker-years to unemployed from employed in years where the worker was employed for fewer than 1,000 hours and later reports that they were unemployed for more than one-quarter of the year.

I winsorize inflation-adjusted income below at $7,000, which is roughly half the full-time federal minimum-wage income. This accounts for incomplete reporting of transfer income such as unemployment benefits. Winsorization of very low incomes is necessary when working with log labor income. I drop a few workers whose income is winsorized in at least half of all observations. I further exclude workers where (i) negative labor income is reported in at least one year (ii) at least 25 percent of (year) observations of labor income are imputed in the PSID or (iii) the average number of hours worked per year when employed is less than 500. Worker-years are excluded where labor income is unavailable or unreliable. Labor income is considered unreliable where (i) it is imputed with a note indicating that the imputation error likely exceeds ten percent of total income or (ii) the reported full-time labor income for the worker in exactly one year lies outside of a range of 20 to 500 percent the median full-time income for the given occupation and is less than half or more than double the worker's median full-time income in other years.

A.2 Construction of Employment Characteristics in $CHAR$

I use sampling weights throughout the construction of the following characteristics so that they best represent the distribution that would result when using the entire population.

- (Relative) Occupational Wage - For each occupation code and year in the PSID, I compute the mean hourly wage using workers who report working in that occupation for at least 1,500 hours in the given year. This wage rate is normalized by the mean wage rate for the year (across all occupations). The relative wage for each occupational code is taken as the median normalized occupational wage rate across the years for which the given occupational code is used.

- Occupation and Industry Based Wage Beta - Workers are sorted into groups separately by occupation and industry of employment, and the average growth in log labor income is computed for each group. These occupation and industry-based log labor income growth rates are regressed upon the aggregate growth in log labor income and a constant term. The coefficient on the aggregate growth rate in log labor income is the "wage beta" for the given occupation or industry. I use only six occupational categories and seven industry categories (matching those found in the SCF) to keep group sizes large enough for wage betas to be estimated accurately.

- Employment Industry Stock Beta - I construct CRSP portfolios for each worker's industry of employment by mapping the two- and three-digit Census industry codes used in the PSID to corresponding SIC code ranges. In cases where Census industry codes map to CRSP portfolios with a median of less than 50 stocks per year, I instead use the next broader SIC category (i.e. one less digit) to construct the portfolio. The employment industry (stock portfolio) beta is estimated by regression of the equity premium of the industry portfolios on the CRSP value weighted equity premium over the period 1968 to present, with equity premia computed from returns by subtracting the three-month US Treasury Bill rate.

A.3 Data Screens and Construction of Variables from SCF Data

I focus on households with reliance on human wealth for which current employment characteristics are available, so I remove households where (1) either the head or spouse is currently unemployed, (2) either the head or spouse is already receiving income from social security or is planning to retire within two years, and (3) the weighted average age of the head and spouse is not between 25 and 60 (using the share of household human wealth as weights). I remove a few further households with difficult to interpret financial situations; where (1) the head and spouse are financially independent, (2) either the head or spouse receives income from secondary employment that exceeds 50% of their income from primary employment, or (3) income in the given year is non-positive and/or less than 10% or more than 1000% of what the interviewee reports as the household's typical annual income. In most analysis, I further restrict attention to those households for which adjusting portfolios for labor income risks could have non-trivial welfare implications. Specifically I exclude households for which financial assets (including individual and employer retirement plans but excluding owned private businesses) are less than one-tenth of human wealth. The SCF data is provided in a multiple imputation form, so if at least one imputed version of the household is excluded by the screens above, I exclude all imputations of that household (so as not to bias the multiple imputation procedure).

In this paper I construct and use the following household level variables for each imputed

SCF household.

- Financial Assets - This the total value of all checking, savings, money market accounts, certificates of deposit, brokerage accounts, bonds, stocks, mutual funds, hedge funds, money owed by others (including businesses), the value of whole life insurance policies, cash value of annuities, trusts, individual retirement accounts, college savings accounts, and employer pension plans (e.g. 401k, 403b, Keogh accounts, defined benefit plans). In some cases, the cash value of annuities, trusts, or other defined benefit plans is unknown. In these instances I use the starting date for the payments (if payments are not already being received), the expected duration of the payments (most commonly using self-reported life expectancy, winsorized at 95), and a constant discount rate. The discount rate is chosen to imply the same yield as is found in other accounts where both the cash value of the plan and cash flows are available. This discount rate ends up being between 4 and 6 percent.

- Stock Holdings - This is the total value of common stock, equity mutual funds, and 80 percent of the value of hedge funds held by the household. I include stock holdings in retirement accounts, which are generally significant. The most recent SCF waves ask respondents what fraction of a given account (e.g. spouse's Roth IRA) is invested in stocks, so I do not have to make assumptions about allocations. However, allocations sometimes vary across imputations, indicating that some respondents were uncertain of their holdings. The standard errors I use account for this source of uncertainty.

- Debt - The total value of mortgages on residential and investment property, auto loans, home equity loans, other consumer loans, credit card debt, loans against retirement plans or insurance policies, and money owed to others, including businesses.

- Private Business - The self-reported value of the respondent's ownership of privately owned businesses.

- Real Estate and Investment Property - The total value of the household's share of residential and commercial buildings and land owned.

- Other Property - The self-reported value of other significant non-financial, non-real estate household property. Most commonly this includes vehicles, art, jewelry, and precious metals.

- Equity - This is computed as the sum of financial assets, real estate and investment property, and other property minus debt. In regressions I winsorize the value below at \$10,000. This affects very few observations given the screen on financial assets relative to human wealth.

A.4 Construction of Human Wealth Estimates for Workers in the SCF

Estimating the value of human wealth is quite complicated. The appropriate discount rate for future labor income depends on dynamics of the labor income process and relative importance of human wealth in maintaining consumption. Huggett and Kaplan (2012) derive discount rates for representative constant relative risk aversion workers from three different education level cohorts. Theoretically, discount rates should also account for the substantial heterogeneity in unconditional labor income risks I document, as well as variations in risk preferences, and background wealth. The appropriate discount rates may be lower or higher for “high risk" careers depending on the extent to which the greater risk tolerance of individuals with such careers offsets the higher risk level of the employment.

However, I primarily use human wealth in this paper as a way of improving the comparability of cross-sectional comparisons. Such analysis is not very sensitive to bias that affects the valuation of all workers’ human wealth. Furthermore, complicated sources of variation in the cross-sectional discounting of labor income are realistically a much less important cause of cross-sectional variation in human wealth than is the variation in size and duration of workers’ projected income streams. As a compromise, I use real discount rates that are representative of the calibration by Huggett and Kaplan. These rates start at 9.25% for workers at age 25 and decline by a constant 0.15% per year, reflecting declining sensitivity to labor income risk as human wealth loses importance over the life cycle. As a robustness check, I find that coefficients from the analysis in Tables 1.6 and 1.7 change by one tenth of a standard error or less when I instead use a constant 4% discount rate to compute human wealth for all workers.

To estimate the income stream to be discounted for each worker, I use the average real income growth by age and educational attainment (high school graduate, BA degree) from the PSID, which produces hump shaped profiles of projected real lifetime earnings. I apply this growth path to the income earned in the present year (which includes self-employment income), unless this income level is reported to be abnormal, in which case I use a self-reported “normal" level of income instead. If the worker is currently employed part time, but reports that they expect to be employed full-time in the future, I multiply income in the expected future full-time employment years by two. Similarly, I halve income in future years where the worker expects to only work part-time, and terminate labor income at the workers self-reported expected retirement age, which is limited by the workers self-reported life expectancy (winsorized at 95).

A.5 SCF Versus PSID Self-Reported Risk Tolerance Measures

In the 1996 PSID, the interviewed family member is asked a series of questions of the form “Suppose that the chances were 50-50 that a new job would double [your/your family] income, and 50-50 that it would cut it by X percent. Then, would you take the new job?," where X is 10, 20, 33, 50, and finally 75. With power utility, this measure has a straightforward theoretical relationship to the risk tolerance parameter, at least when labor income risk is ignored.[1] It has also been shown to explain a wide variety of risky behavior (see Barsky 1997).

I find that the PSID and SCF risk tolerance measures relate similarly to worker demographics and employment characteristics. Specifically, I create a risk tolerance proxy from

[1]With parametric assumptions about the form of the measurement error and a way to estimate it (e.g. repeated observations), an estimate of the actual risk tolerance parameter can be obtained (see Kimball 2008).

the PSID responses that is similar to the SCF-based proxy I use in Table 1.8. The proxy equals -1 if the interviewee refuses an offer of X equals 10 percent, 1 if the interviewee accepts an offer of X equals 33 percent, and 0 otherwise. I then instrument both this PSID proxy and the SCF-based proxy from Table 1.8 using the set of worker demographics and employment characteristics $CHAR$, and compare the two instrumented risk preference proxies using the distribution of $CHAR$ across PSID and SCF households. The correlation of the instrumented proxies across households is about 0.6.

I proceed in the text using the SCF measure as this measure is available for a substantially larger cross-section of usable households (8,315 versus 2,352). As a result, my analysis has much greater statistical power when using the SCF measure, and there is little power to spare. I do confirm that using an instrumented PSID measure also results in (1) a switch in sign from positive to negative for the coefficient on permanent income variance in stock allocation and leverage regressions and (2) statistically insignificant coefficients on the other three labor income risks. However, standard errors are large, so little can be said conclusively.

A.6 Endogeneity Bias Analysis

Suppose the correct equation to estimate household financial risk is given by Equation (A.1), where the impact of labor income risk on financial risk, α_0, is the coefficient of interest. Demographic controls are decomposed into observed demographics, Dem, and unobserved demographic variation, $UnobsDem$, that predicts financial risks and is orthogonal to Dem by construction. Additional control variables, such as year dummies, are included in $OtherControls$.

$$FinRisk = \alpha_0 LabRisk + \alpha_1 Dem + \alpha_2 OtherControls + UnobsDem + \epsilon \tag{A.1}$$

However, I can only estimate Equation (A.2) since $UnobsDem$ is unobserved.

$$FinRisk = \hat{\alpha_0} LabRisk + \hat{\alpha_1} Dem + \hat{\alpha_2} OtherControls + \hat{\epsilon} \tag{A.2}$$

If *UnobsDem* is correlated with either *OtherControls* or *LabRisk*, then $\hat{\alpha_0}$ is a biased estimate of α_0. This bias is given by the standard formula in Equation (A.3). $\widetilde{LabRisk}$ is the residual of *LabRisk* from the regression $LabRisk = \hat{\beta}_0 Dem + \hat{\beta}_1 OtherControls$.[2]

$$\hat{\alpha_0} - \alpha_0 \rightarrow \frac{\sigma(\widetilde{LabRisk}, UnobsDem)}{\sigma^2(\widetilde{LabRisk})} \tag{A.3}$$

Following Altonji, Elder, and Taber (2005), I assume that the endogeneity of labor income and financial risks with respect to observed demographics is comparable to the endogeneity of labor income and financial risks with respect to unobserved demographics. Specifically, I make the assumption in Equation (A.4) below: the coefficient from a univariate regression of labor income risk (or other demographic controls) is the same when *UnobsDem* is the right hand side variable as it is when the right hand side variable is the part of observed demographic controls which predict financial risks, $\hat{\alpha_1} Dem$.

$$\frac{\sigma(X, UnobsDem)}{\sigma^2(UnobsDem)} = \frac{\sigma(X, \hat{\alpha_1} Dem)}{\sigma^2(\hat{\alpha_1} Dem)} \text{ where } X \text{ is } LabRisk, OtherControls \tag{A.4}$$

With this assumption, the estimated bias can be rewritten as Equation (A.5) below. The first term in parenthesis can be estimated, and is large when observed variables are an important source of endogeneity. To estimate the endogeneity of observed demographics more precisely, I add 34 new household variables to the existing baseline variables in *Dem*.[3] However, adding these variables and/or using a randomly selected half of the variables now in *Dem* makes relatively little difference to the estimate of the first term. The second term represents the relative importance of unobserved demographics in explaining financial risks. This term is unknown, but presumably is not too large given that the demographic

[2]These formulas in this appendix apply to least squares regressions whereas I run tobit regressions. However, in the data I use, censored values are uncommon, so least squares and tobit regressions yield very similar results. Therefore I view the formulas in this appendix as approximately true for the regressions I run.

[3]Examples of these variables include whether the head is divorced, latino, asian, holds an advanced degree, measures of household mobility and health, the use of financial planning software, and controls for reasons for saving.

variables of most obvious importance, such as education level, are included in *Dem*.

$$E[\hat{\alpha}_0 - \alpha_0] = \left(\frac{\sigma(LabRisk - \hat{\beta}_1 OtherControls, \hat{\alpha}_1 Dem)}{\sigma^2(\widetilde{LabRisk})} \right) \left(\frac{\sigma^2(UnobsDem)}{\sigma^2(\hat{\alpha}_1 Dem)} \right) \tag{A.5}$$

In Table A.1, I report the coefficients $\hat{\alpha}_0$ estimated in Tables 1.6 and 1.7 along with the estimated bias that results when unobserved *UnobsDem* is as important in predicting financial risks as is the observed *Dem*. Bold type indicates coefficients previously identified as statistically significant. The estimated impact of permanent income variance is largely unaffected by the observed demographics (including the 34 new variables), and as a result the estimated bias is quite modest. Unobserved variation in demographics would need to be roughly ten times (e.g. -3.38/-0.38=8.89) as important as variation due to observed demographics in order to explain the magnitude of the statistically significant coefficients.

Table A.1: *Estimate of Omitted Variable Bias in Regressions with Full Set of Controls (Specifications [4])*

Dependent Variable	$\hat{\alpha}_0$	Bias ($E[\hat{\alpha}_0 - \alpha_0]$) per $\sigma(UnobsDem) = \sigma(\hat{\alpha}_1 Demog)$
Stock Share of Financial Assets X 100, Table 1.6A		
Permanent Income Variance ($\sigma^2(\zeta)$)	-3.16	0.07
Disaster Risk (Job Loss)	0.80	1.40
Permanent Income Cyclicality	2.26	-1.22
Permanent Income Variance (Counter) Cyclicality	-2.77	1.42
Stock Share of Financial Plus Human Wealth X 100, Table 1.6B		
Permanent Income Variance ($\sigma^2(\zeta)$)	**-3.38**	-0.38
Disaster Risk (Job Loss)	1.18	1.06
Permanent Income Cyclicality	1.25	-0.49
Permanent Income Variance (Counter) Cyclicality	-1.41	0.34
Household Leverage X 100, Table 1.7		
Permanent Income Variance ($\sigma^2(\zeta)$)	**-12.67**	-1.24
Disaster Risk (Job Loss)	5.03	5.20

Appendix B

Appendix to Chapter 2

B.1 Classification of Investor Account Geography (Urban/Rural/Semi-Urban)

We provided NSDL with a mapping of PIN codes (Indian equivalent of ZIP codes) to an indicator of whether the PIN is a rural, urban, or semi-urban geography. To make this determination, PIN codes were matched to state and district in an urbanization classification scheme provided by Indicus. In cases where urbanization at the district level is ambiguous, we use use postal data, noting that the distribution of number of large postal branches and small sub-branches in a PIN is markedly different in urban and rural geographies.

B.2 Stock Data

We collect stock-level data on monthly total returns, market capitalization, and book value from three sources: Compustat Global, Datastream, and Prowess. Prowess further reports data sourced from both of India's major stock exchanges, the BSE and NSE. In addition, price returns can be inferred from the month-end holding values and quantities in the NSDL database. We link the datasets by ISIN.[1]

[1] Around dematerialisation, securities' ISINs change, with some data linked to pre-dematerialisation ISINs and other data linked to post-dematerialisation ISINs. We use a matching routine and manual inspection to

To verify reliability of total returns, we compare total returns from the (up to three) data sources, computing the absolute differences in returns series across sources. For each stock-month, we use returns from one of the datasets for which the absolute difference in returns with another dataset is smallest, where the exact source is selected in the following order of priority: Compustat Global, Prowess NSE, then Prowess BSE. If returns are available from only one source, or the difference(s) between the multiple sources all exceed 5% then we compare price returns from each source with price returns from NSDL, We then use total returns from the source for which price returns most closely match NSDL price returns, provided the discrepancy is less than 5%.

After selecting total returns, we drop extended zero-return periods which appear for non-traded securities. We also drop first (partial) month returns on IPOs and re-listings, which are reported inconsistently. For the 25 highest and lowest remaining total monthly returns, we use internet sources such as Moneycontrol and Economic Times to confirm that the returns are indeed valid. The resulting data coverage is spotty for the very smallest equity issues, which could lead to survivorship issues. Therefore, in computing account returns we stock-months where the aggregate holdings of that stock across all account types in NSDL is less than 500 million Rs (approximately $10 million) at the end of the prior month.

We follow a similar verification routine for market capitalization and book value, confirming that the values used are within 5% of that reported by another source. Where market capitalization cannot be determined for a given month, we extrapolate it from the previous month using price returns. Where book value is unknown, we extrapolate it forward using the most recent observation over the past year.

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match multiple ISINs for the same security.

Appendix C

Appendix to Chapter 3

C.1 Daily Frequency Stock Data

Data for stocks with primary listing and company headquarters in the US are from the Center for Research in Security Prices (CRSP).

I exclude all non-common stocks and securities not traded on one of the three major exchanges (NYSE, AMEX, and NASDAQ). I then link the CRSP dataset to Compustat, and use the Compustat historical SIC codes to map stocks to industries. When not available, I use SIC codes provided by CRSP. I exclude shares of companies that are headquartered in locations other than their primary trading venue using the primary issue and headquarters location tags from Compustat. I also exclude all issues that are indicated as other than primary issues in the Compustat database. I further exclude stocks classified in the industries that are removed from the international (Compustat) dataset (SIC codes starting 672, 673, or 679), as most securities matching these SIC codes are not common stock. Stocks are adjusted for delisting returns, assuming returns of -40 percent or 0 percent where the delisting is missing, depending upon whether the delisting was performance related. However, including delisting returns has no meaningful impact on any of the results or conclusions.

Data on securities with primary listings outside the US are from Compustat Global.

In this data, I associate a security with a country when that security trades in that country's markets, is priced in the common currency(s) used in the country's local equity markets, and is headquartered in the country. This means that a relatively small number of companies that have primary listing and headquarters in different countries will be excluded from all portfolios. I then remove all securities that Compustat indicates do not participate in the parent company's earnings, as well as securities that are mutual funds, trusts, multi-sector holding companies, or fixed income. For this latter exclusion, I rely on Compustat's issue type code (excluding all but common equity when indicated), industry classifications, and security names. I exclude SIC codes beginning 672, 673, and 679 (investment offices, trusts, and miscellaneous investing activities). I screen names using a substantial list of terms (e.g. "FND" and "YIELD") obtained by inspection of random samples of the remaining names until the remaining sample contains no securities with suspect names.[1] The vast majority of securities excluded on the basis of name fall within one of the excluded industry categories. I also remove cross-listed stocks that primarily trade on another country's stock exchanges, as well as secondary issues trading in the same country as a more primary issue.[2] I then convert all financial figures to US dollars using historical exchange rate series obtained from Global Financial Database.

I next employ a series of fixes and further exclusions to remove suspect data. I remove a few securities with prices, returns, or shares outstanding that do not appear to be adjusted at the proper time for currency splits (in Argentina, Mexico, Poland, Peru, Russia, and Turkey) or currency conversions (Euro area countries).[3] I adjust prices and returns for share splits in a few instances where they appear to be unadjusted.[4] I adjust shares outstanding where Compustat indicates that a significant split or share adjustment has occurred but

[1] I use the name based screens suggested by Griffin, Kelly, and Nardari 2009 as a starting point.

[2] Primary issues are identified using the Compustat "PRIROW" tag.

[3] I drop Brazilian data available prior to 1996 as handling of several currency splits makes fixing the data quite complicated.

[4] I adjust based on the change in outstanding shares where the absolute log changes in shares outstanding and allegedly split adjusted prices both exceed 0.67 and where the sum of the two is less than 0.2. Also, in a few instances some, but not all, share classes of an issue appear to be properly split adjusted, so these adjustments are carried over to the primary share class (if applicable).

shares outstanding are not adjusted.[5] I remove remaining large returns that occur at the same time as large changes in shares outstanding, suggesting a share adjustment may not have been accounted for properly.[6] Similarly, I exclude cases where returns are large, but the price change is not, suggesting a faulty share adjustment factor.[7] I use more recent share counts in cases where shares outstanding decline drastically without accompanying changes in price.[8] I remove observations of very large returns that reverse to previous prices on the following day, suggesting either data error or extreme bid-ask bounce.[9] Finally, I correct prices (and returns) in cases where both shift by almost exactly a multiple of 10, suggesting a change in quotation or shifted decimal.[10]

I then take the repaired data and define market days as those for which the number of stocks with current transaction prices available is at least 50 percent of the monthly moving average. I then exclude observations on other days. Out of concern about using infrequently traded issues, I remove a stock from the dataset if more than half of the sequential price pairs available are not on adjacent market days, or if more than 10 percent of the sequential price pairs are more than one week apart.[11] I also exclude all stocks that indicate at least one daily return exceeding either -95 percent or 400 percent. A manual check of 100 randomly drawn extreme returns from the remaining distribution suggests that the fixes detailed

[5]I only make this change where the adjustment is to reduce shares outstanding, so as to avoid potentially overweighting issues with this data adjustment.

[6]Specifically, where absolute changes in both log shares and log returns exceed 0.67.

[7]I search for cases where the log adjusted price moves by more than 0.4, but the log price moves by less than 0.1.

[8]I find cases where the log share count and market capitalization both change by more than -1.5, and log returns are less than 0.3. I do not backwards adjust case where share counts increase drastically without changes in price, as this may lead to erroneously overweighting very small stocks.

[9]I search for absolute log returns exceeding 0.67 with two-day returns less than 25 percent of that amount.

[10]Specifically, I look for cases where the ratio of subsequent adjusted price is between 0.9 and 1.1 times a non-zero power of 10 and correct by that power of ten. The exception is returns of -90 percent, which are conceivably not data errors. In this case I only correct returns of exactly -90 percent.

[11]Throughout the paper, calculations of portfolio returns are based on only those observations of prices on adjacent market days, but I do track the fraction of the capitalization of the total portfolio that the included returns reflect.

above are successful in removing erroneous extreme returns.

C.2 Construction of Variables Measuring Attributes of Portfolios and Portfolio Pairs

Size of Industry Portfolio where News is From

I first compute the market capitalization of each industry within each market for each year and month as the sum of the median market capitalization (over the course of the year or month) of the stocks in that market and industry. The size of the industry is taken as a fraction of the total size of the industry summed across the 55 markets. I use the natural log of this value and then scale the result so that the cross-sectional standard deviation equals one. There are no negative outliers (very small portfolios) as all portfolios generating news represent at least one percent of the global industry market capitalization

(Log) Volatility of Excess Industry Returns and News

Volatility is measured using moving average standard deviations over the most recent 60 trading days. These standard deviations are estimated assuming mean daily excess returns or news of zero (i.e. using squared news terms rather than squared deviations of news terms about the mean). I use natural logs of these estimates in regressions.

Exports to Market where Industry News is From

Data on the annual value of exports by ISIC code is from the United Nations Comtrade database. Data on production by ISIC code is from the United Nations INDSTAT3 database. All data are in terms of constant (2000) US dollars, and span 1986 through 2009. I merge these databases and then use concordances from Statistics Canada to map ISIC codes to the SIC codes on which Fama-French industries are based. Some ISIC codes are mapped to multiple SIC codes. In these cases, I allocate the exports and production across such SIC codes in proportion to the market capitalization by SIC code in the given country. For each pair of countries, industry, and year, I compute the fraction of the industry's output exported to each given foreign country in each year.

Unfortunately, the UN databases only cover manufacturing industries, and do not have coverage for some industries across some country pairs and years. To supplement this data, I obtain data on the annual value of exports (in constant, year 2000 US dollars) by origin and destination from the International Monetary Fund's Direction of Trade database.[12] I also obtain GDP data from the World Bank. For country pairs, industries, and years where UN data is unavailable I compute an alternative figure as total exports to a given country divided by the GDP of the exporting country. If UN data is available for the given industry, just not the given country pair and year as well, I apply an industry and year specific modifier this ratio; multiplying by the fraction of the industries production exported, and dividing by the fraction of all industry's production exported.

To reduce the role of outliers, I winsorize the resulting export-output ratios at the 5th and 95th percentiles, and then take natural logs. The measure is then scaled to a standard deviation of one. Regression coefficients based on UN data derived measures are similar to regression coefficients based on measures based on IMF data, so mixing the measures does not significantly affect results.

Correlations of Return on Equity (Industry Fundamentals)

I first use accounting data from Compustat to calculate industry return on equity for each country and year as industry level income divided by industry level shareholder equity. In the calculation I exclude firms with negative shareholder equity as well as firms with return on equity exceeding positive or negative 100 percent. To convert industry level return on equity to industry-specific return on equity, I subtract out the industry-weight adjusted

[12]This data is missing export statistics for Taiwan. The missing Taiwan data is provided beginning in 1995 from the Statistical Yearbook of China, and covers most trading partners. Trading partner data missing from the Statistical Yearbook of China (used for Taiwan data) is extrapolated as the average of the export share of GDP from two other small Asian exporting entities, Singapore and Hong Kong, which generally have similar export shares to Taiwan where data on both is available.

market return on equity.[13]

An alternative at this point is to compute a moving average comovement or correlation of the returns on equity by country-pair and industry. However, these measures are very noisy due to outliers produced by small industry portfolios, and there is a tradeoff between estimating the comovement more precisely using a longer time series and capturing potential dynamics in the strength of the fundamental connections. Furthermore, some smaller country-industry pairs do not have sufficient accounting data in Compustat, both of which would necessitate some extrapolation.

Instead, I predict correlations. To do this, I normalize the industry-specific return on equity measures by country and industry and compute the product of these normalized measures for each industry and year across country pairs. This country-pair, industry, year product is then predicted in a linear regression by industry, year, and country pair dummy variables. I produce fitted values from the country pair and industry dummies, and then scale these to a standard deviation of one for use as a measure of cross-border ties in industry fundamentals.

Common Language

Using Google searches and websites including Paul Lewis' Ethnologue and the CIA World Factbook, I determine the primary languages spoken in each country. I also determine the languages which are fluently understood by at least one quarter of the population, which I classify as secondary languages if they are not primary. I construct a dummy variable equal to one where at least one of the primary language(s) of the country producing the signal is a primary or secondary language in the responding country. Regression results are similar when the foreign and local country are required to share at least one primary language.

Analyst Coverage Overlap

[13] Industry-weight adjusted return on equity is a weighted average return on equity across industries in which the weights for each industry are in proportion to the industry's share of the global market capitalization. As with construction of industry-adjusted abnormal returns, I do not allow the weight on a given industry to increase by more than five times to avoid producing excess noise from large weights to very small industries.

The statistic I produce is the fraction of the capitalization of the given country and industry portfolio which is covered by at least one equity analyst who simultaneously covers equities in the country from where the industry news is from.[14] An analyst is defined as covering a stock if he has produced an earnings estimate or recommendation on the stock at some point in the past year. Analyst coverage data is from IBES, and is matched to stocks in Compustat and CRSP by ISIN/SEDOL and CUSIP respectively. Where matches to the CRSP and Compustat data are not found, the country of the rated issue is identified by IBES ticker, ISIN header, and the IBES "usfirm" flag. Analysts are found following stocks in all countries used in the analysis except Bangladesh. I do not compute analyst coverage overlap prior to 1990 as the IBES coverage level appears to drop off sharply prior to that date.

Cross-Border Equity Holdings

I obtain data on cross-country equity holdings from the International Monetary Fund's Coordinated Portfolio Investment Survey (CPIS). For each country pair (countries A and B), I compute the scaled measure of holdings below.[15]

$$\text{Holdings Overlap} = \frac{\text{Country A holdings of Country B equity} \times \text{Country B holdings of Country A equity}}{(\text{Country A GDP} \times \text{Country B GDP})^2}$$

The motivation for the scaling is that simple economic models would generally suggest that the value of holdings of one country in another country in equilibrium should be proportional to the economies of both countries. CPIS data is only available back to 2001 (through 2009).

This measure contains large outliers where small countries have substantial cross-holdings (e.g. Portugal and Ireland, Kuwait and Jordan, and Hong Kong and Singapore) or where cross-holdings are approximately zero. I therefore winsorize each part of this ratio

[14]Only about 15 percent of analysts in IBES cover issues in multiple countries for at least one year.

[15]The foreign holdings of thirteen of the countries, all among the smallest except for China and Taiwan are unavailable. For these countries, I excluded the missing observation from the numerator of the computed ratio, do not square the denominator, and multiply the result by the square root of the sample mean.

(i.e. scaled holdings of A in B, and scaled holdings of B in A) at 0.01 and 5. I then take the log of the result and scale to a standard deviation of one.

Cross-Listings

I define a measure (given by $Xlist_{A,B}$) which incorporates both the extent to which country A's stocks are listed on a major exchange in foreign country B as well as the extent to which companies headquartered in A choose to make their primary stock listing in a country B. The variable I use in the analysis for country pair A-B, is equal to the average of $Xlist_{A,B}$ and $Xlist_{B,A}$, which are computed separately for each calendar year, industry, and country pair. This variable is bounded by zero and one.

$$Xlist_{A,B} = \frac{(\text{Capitalization of Country A Companies Cross-Listed in B + Capitalization of Companies HQ in A, Primarily Listed in B})}{(\text{Capitalization of Country A Companies + Capitalization of Companies HQ in A, Primarily Listed in B})}$$

Headquarters location and primary issue trading location are determined from Compustat. Note that companies with different headquarters and trading locations do not appear in any of the industry portfolios. Such cases are far less common than cross-listings, but there are a few country pairs, most notably Hong Kong and China, for which a significant number of companies are headquartered in one and trade primarily in the other.

I use two sources of data to determine where cross-listings exist. The first is Compustat Global, which indicates multiple trading venues for many major issues. This data is linked with CRSP, which contains pricing data for cross-listings on the major US exchanges. I also use a dataset of global cross-listings constructed by Sergei Sarkissian and available from his website. These listings were matched to Compustat and CRSP data by company name, with substantial manual matching employed.

Size of Stocks in Portfolio Responding to the News

The size of stocks in each industry portfolio is computed as the value weighted average market capitalization of stocks in the portfolio. I take the natural log of this measure and scale it so that the standard deviation is equal to one.

PRS Risk Index for Responding Market

The Political Risk Services (PRS) Group publishes several indices measuring country-specific risks that might concern foreign investors. I use the PRS Investment Profile index, which measures risk to operations, taxation, repatriation, and labor costs that face foreign investors. I multiply the index by negative one (so that higher levels correspond to greater risk) and scale the index to have a standard deviation of one prior to its use in the regressions.

Trading Hours Overlap

Historical trading hours for each market are determined by a combination of searches in both Google and Factiva. For each date and market pair I compute the number of hours for which trading in the two markets overlaps.[16] This statistic is divided by the lesser of the number of hours traded in the pair of markets, resulting in a number ranging between zero (when there is no overlap in trading hours) to one (when one market's hours are a subset of the other's). Adding a dummy variable for where the overlap is positive has negligible incremental explanatory power for responses, so it is not included.

Turnover

Share turnover is computed from Compustat and CRSP data as the market value of shares (at the current price per share) traded over the past year divided by the current market capitalization of the portfolio. This statistic is divided by 12 to represent monthly turnover. Turnover for about 0.1% of observations (which are disproportionately extreme outliers) is truncated at 100% per month. Due to availability, I compute portfolio turnover beginning in 1995.

Cultural Distance

[16] I also track whether, and for which years, the country adheres to daylight savings time. A few countries that do not adhere to daylight savings time nonetheless adjust their market trading hours to correspond to daylight savings time.

I obtain an index of each country's traditional or secular-rational values and an index of survival or self-expression values from the World Values Surveys (conducted 1981 to present and available at www.worldvaluessurvey.org). The survey designers conclude that these two cultural dimensions capture a great deal of the cross-country variation in a range of cultural measures. These values indices are scaled to a standard deviation of one. Cultural distance between two countries is measured as the sum of squared differences in the two indices (where the most recent survey as of the given year for each country is used), which is then scaled to a standard deviation of one.

Adjacent Country Dummy

The adjacent country dummy is set equal to one iff the countries in a given pair border each other directly on land, or directly across a relatively narrow (less than 500 mile) stretch of water (e.g. the United Kingdom and France).

C.3 Industry News Construction Across Markets with Asynchronous Trading Hours

Most stock markets are not open at the same time, with trading hours with overlap some or not at all. To make this determination, I collected the time-series of each of the 55 stock market's hours of operation (1986-2010) from a variety of sources through web searches on Google and Factiva.

With asynchronous trading, I do not assume that all elements of $\Phi(-1, i, t)$ are zero when setting up equations to estimate β (e.g. Equation (3.3)). Specifically, the only elements of $\Phi(-1, i, t)$ which are set equal to zero are those corresponding to news generated in a market that closes no later than the responding country's market (i.e. where the news could have been responded to on day $t-1$). Also, I set elements of $\Phi(0, i, t)$ equal to zero where they correspond to news generated in a market which opens after the responding country's market on day t (i.e. where the news cannot be responded to until trading day $t+1$). In some cases where trading hours overlap, the country pair may correspond to non-zero elements in both $\Phi(0,i,t)$ and $\Phi(-1,i,t)$. To account for this, the controls in X include a measure of the extent to which trading hours overlap on the given day in the countries generating and responding to news. A final tweak to the assumption used to identify β in this setting is that industry news is now assumed to also be orthogonal to a one-day lag of news in countries with markets which close earlier in the day.

Once the β are estimated, the fact that $\Phi(-1,i,t)$ is non-zero means that Equation (3.5) for industry i is adjusted to Equation (C.1) below.

$$Z(i) =^{argmin}_{Z^*(i)} ||Z^*(i) - [\hat{\Phi}(0,i,t) + \hat{\Phi}(-1,i,t)(L)]^{-1} R^{ex}(i)|| \text{ s.t. } z_{c_1}(i) \perp z_{c_2}(i) \tag{C.1}$$

s.t $z_{c_1}(i) \perp z_{c_2}(i)$ (and $z_{c_1}(i)_t \perp z_{c_2}(i)_{t-1}$ if markets in c_1 close after those in c_2)

C.4 Responses to Within Country Industry News

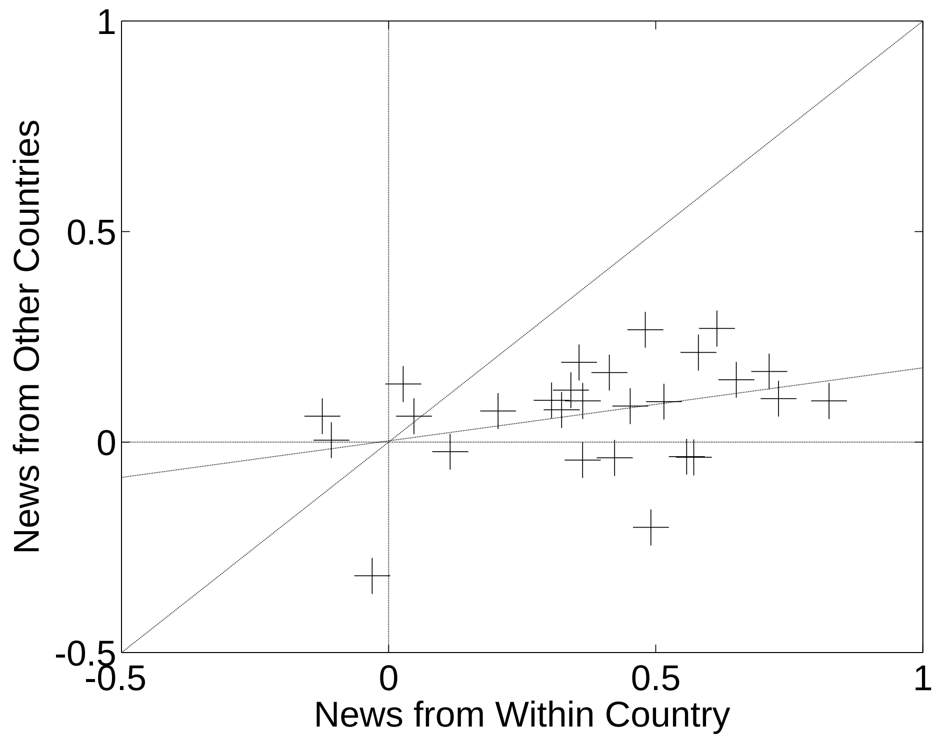
I split each country's portfolios randomly in two, forming two fictitious markets where there really is one.[17] Stocks are assigned to one portfolio or the other in a random way stratified by size to ensure that the market capitalizations of the two portfolios are comparable. I then compute excess industry returns to both portfolios, using the same industry adjusted market benchmark used elsewhere for adjusting stock returns in the country. Next, I define news from each half of the portfolio by singular value decomposition; setting industry news as the set of orthogonal vectors closest to the excess industry returns.

For each of the two halves of the original industry portfolio for each country, I regress excess industry returns from day t through day $t+1$ or $t+30$ on the day t industry news from the other half of the country's industry portfolio. These coefficients are averaged across both halves of each country, and are defined as the initial and total response to within country industry news. The difference between the two sets of coefficients defines the delayed response to within country industry news.

Figure C.1 plots the ratio of delayed to total (30-day) response from these within-country

[17] I thank Jeremy Stein for suggesting this.

Figure C.1: *Cross-Country Comparison of Ratios of Delayed to Total Response to Industry News: News from Within the Same Country versus News from Other Countries*



Delayed response is given by the difference between initial (day t through $t+1$) and total (days t through $t+30$) responses of excess industry stock returns to industry news derived from regression Equation 3.6. Results are only shown for the larger half of the 55 countries, as estimates are considerably less precise for the smallest markets.

regressions against the same ratio derived from responses to industry news from other countries. The fact that most points lie well below the diagonal shows that a significantly greater fraction of the response to cross-border news comes in the form of drift.

While this procedure does not explicitly test the possibility that inefficiency is driven by distance, (which is typically greater across than within borders) distance based inefficiency is unlikely to be the driver. First, in the multivariate analysis, adjacency of countries has fairly limited marginal explanatory power for response size and appears unrelated to the response speed of stock returns to industry news. Second, there is a negative correlation between a country's geographical size and its inefficiency with respect to within-country signals (i.e. the output of this test).

C.5 Rationally Allocated Attention as an Explanation for the Impact of Common Analyst Coverage and Cross-Listings on Stock Return Response Speed

Suppose that the delayed response (previously $\theta(2,30)X = (\theta(30) - \theta(1))X$) can be expressed in two parts. The first part, $f(\theta(30)X)\theta(30)X$ is due solely to the importance (total response) of the news, and the second part $\tilde{\theta}(2,30)X$ is unrelated to the news importance and is explained by other features of X that enhance information flow or affect the cost of arbitrage. With this in mind, I rewrite the delayed to initial response ratio as Equation C.2 below.

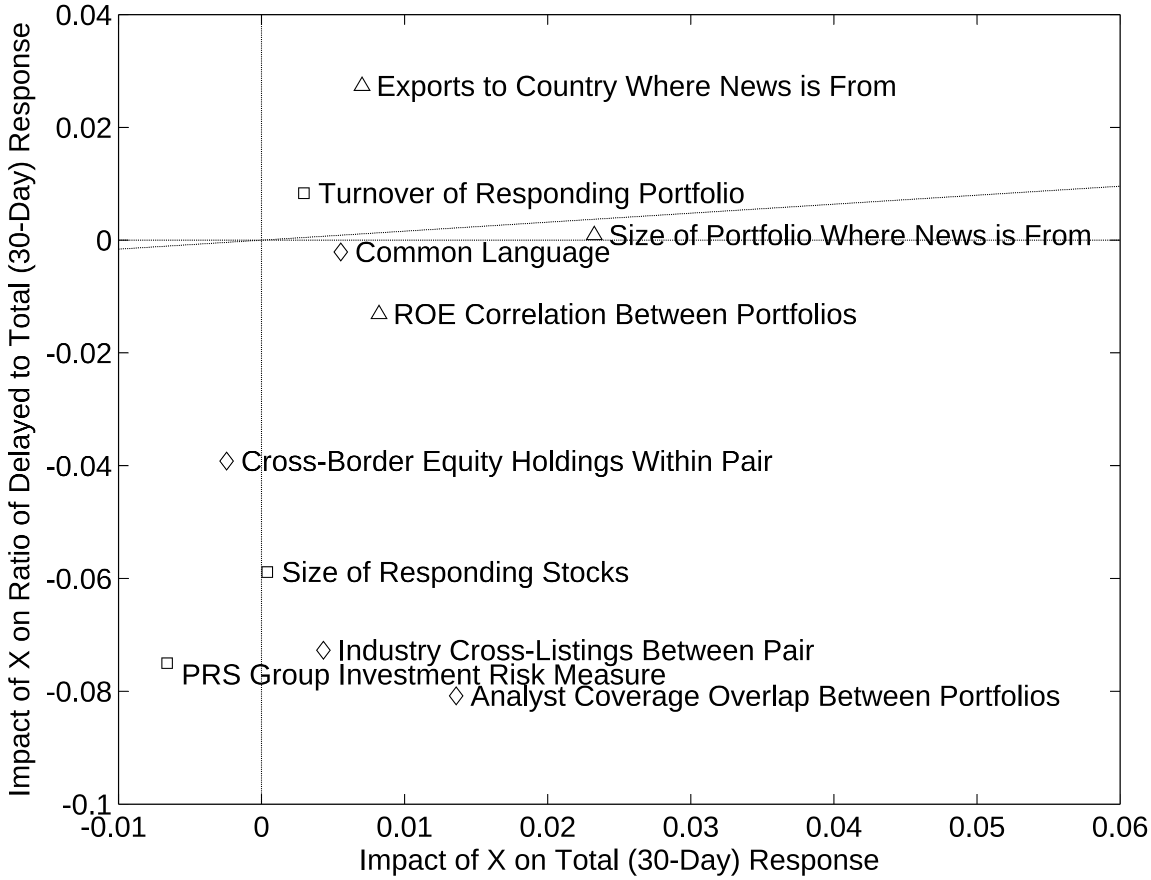
$$DELAY(i,c1,c2,t) = f(\theta(30)X(i,c1,c2,t)) + \frac{\tilde{\theta}(2,30)X(i,c1,c2,t)}{\theta(0,30)X(i,c1,c2,t)} \tag{C.2}$$

If the mere importance of news generates significant investor attention and increases the trading activity of arbitrageurs, then $f()$ should be a decreasing function of the news size. Now, consider a variable X_j that affects the delay-initial response ratio only through the “rational attention" channel $f()$ so that $\tilde{\theta}(2,30)_j = 0$, and $\Delta DELAY_j = f'()\theta(0,30)_j$. A few candidates for such an X_j are the size of the portfolio the news is from and the two measures of fundamental ties: exports to the country the news is from, the estimated return on equity correlation of portfolios.[18]

Figure C.2 plots the impact of variables on the delayed-total response ratio (vertical axis) against the impact of those variables on the total response size (horizontal axis). The variables (relating to fundamental ties) that are proposed to affect the response ratio only through f are indicated by triangular icons. For these variables, there is little relationship between the impact of variables on the total response size and the impact on the ratio of delayed to total response as indicated by the slight slope of the line in Figure C.2. This weak relationship suggests that f' is small and rational attention is not a likely explanation for the

[18]These variables can also be pre-orthogonalized with respect to measures of information links across borders.

Figure C.2: $\Delta DELAY$ *and Impact on 30-Day Response Sizes* ($\theta(0,30)$) *Estimated from Equation 3.7*



$\Delta DELAY$ is the impact of a one standard deviation change in variables X on the estimated ratio of delayed (days $t+2$ through $t+30$) to total 30-day (days t through $t+30$) excess industry stock return responses. Return responses (and the impact of X on return responses) are estimated using Equation 3.7; regressions of excess industry stock returns on preceding news from other countries.

results. In contrast, the variables measuring information links between portfolios (indicated by diamond icons), such as common analyst coverage, require a strong rational attention effect (i.e. a steeply downward sloped f) in order to be satisfactorily explained.

C.6 Supplementary Tables and Figures

Table C.1: *Market Coverage by Country*

I compute aggregate market capitalization as the sum of the market capitalizations of the included stocks, which are computed in turn as the median market capitalization given by closing (or last available) prices in the given month. This results in slightly different estimates as compared with computing the aggregate market capitalization for each day and taking the median, but the latter method is complicated by the fact that capitalization is not calculable for a subset of the stocks on any given day. Historical market capitalization figures are from the World Federation of Exchanges (http://www.world-exchanges.org/statistics). These figures do not consistently include the capitalization of stocks listed on smaller stock markets. Therefore, the capitalization ratio is unavailable for several countries, and there are a few instances where the market capitalization of the stocks used exceeds that accounted for by the WFE. For example, WFE capitalization for Japan in 1990 and 2000 does not include the Osaka exchange or JASDAQ.

		Industries Represented	Market Capitalization Covered (Billions USD)			Capitalization Covered / Capitalization per WFE		
Country	Years Used	Fama French 49 [3]	Nov 2010	Dec 2000	Dec 1990	Nov 2010	Dec 2000	Dec 1990
United States	1986-2010	47	13,495	14,122	2,702	0.81	0.93	0.87
Japan	1986-2010	46	3,613	3,485	2,835	0.95	1.10	0.97
China	1994-2010	46	3,037	59		0.77		
United Kingdom	1986-2010	47	2,545	2,406	741	0.76	0.92	0.87
France	1986-2010	46	1,716	1,269	274			
India	1989-2010	47	1,636	132	17	[1]		
Hong Kong	1986-2010	46	1,495	439	55	0.55	0.70	0.65
Germany	1986-2010	44	1,356	1,112	329	1.03	0.88	0.93
Australia	1986-2010	47	1,175	306	88	0.90	0.82	0.82
Switzerland	1986-2010	39	1,021	667	76	0.91	0.84	0.48
South Korea	1989-2010	46	1,002	157	45	1.01	1.06	0.41
Brazil	1996-2010	43	884	115		0.61	0.51	
Taiwan	1988-2010	43	797	266	94	1.10	1.08	0.96
Russia	1996-2010	25	698	37		0.85		
Spain	1986-2010	41	631	362	92	0.59	0.72	0.83
Italy	1986-2010	43	560	643	130		0.84	0.87
South Africa	1986-2010	40	462	112	65	0.56	0.85	0.48
Sweden	1986-2010	45	454	279	27		0.85	0.29
Singapore	1986-2010	46	420	137	27	0.69	0.88	0.79
Mexico	1991-2010	27	389	98		0.90	0.78	
Malaysia	1987-2010	45	374	114	39	0.97	1.00	0.81
Netherlands	1986-2010	39	345	576	109			
Indonesia	1990-2010	39	339	19	6	1.00	0.69	0.76
Turkey	1990-2010	37	320	60	10	1.05	0.86	0.55
Saudi Arabia	2002-2010	25	319			0.94		
Thailand	1988-2010	43	268	27	22	0.99	0.91	1.04
Chile	1993-2010	27	243	43		0.74	0.72	
Norway	1989-2010	36	241	56	18	0.98	0.85	0.67
Belgium	1986-2010	39	220	133	34			
Denmark	1986-2010	31	196	90	23		0.83	0.60

[1] Many of the largest companies in India are listed on both the Bombay and National Stock Exchange, each of which is a bit smaller than the capitalization of Indian stocks covered here.

Continued on next page.

Table C.1: *(Continued) Market Coverage by Country*

		Industries Represented	Market Capitalization Covered (Billions USD)			Capitalization Covered / Capitalization per WFE		
Country	Years Used	Fama French 49 [3]	Nov 2010	Dec 2000	Dec 1990	Nov 2010	Dec 2000	Dec 1990
Finland	1987-2010	37	194	287	10		0.98	0.45
Israel	1995-2010	38	189	47		0.91	0.72	
Poland	1994-2010	42	177	28		1.02	0.88	
Austria	1989-2010	33	107	23	22	0.98	0.77	0.84
Kuwait	2004-2010	21	106					
Philippines	1993-2010	34	103	13		0.73	0.50	
Portugal	1992-2010	26	84	66				
United Arab Emirates	2005-2010	16	83					
Greece	1989-2010	39	69	93	8	1.05	0.87	0.55
Egypt	1998-2010	25	64	12		0.78		
Morocco	2001-2010	22	62					
Ireland	1991-2010	24	61	68		1.13	0.83	
Peru	1997-2010	14	51	3		0.55	0.31	
Nigeria	2001-2010	24	48					
Bangladesh	2003-2010	30	47					
Argentina	1989-2010	22	46	37	4	0.81	0.80	1.02
Pakistan	1994-2010	30	34	4				
Jordan	1999-2010	29	27	4		0.89		
New Zealand	1991-2010	37	27	11			0.62	
Vietnam	2007-2010	38	26					
Croatia	2005-2010	25	18					
Sri Lanka	1990-2010	31	16	1	0	0.82	0.51	0.43
Oman	2004-2010	15	15					
Cypress	1999-2010	16	7	9		0.99		
Bulgaria	2007-2010	23	3					

Table C.2: *Mean Coefficients β on Variables X Used to Estimate Response Coefficients (ϕ) in the Derivation of Industry News, $\phi = \beta X$*

Mean β is estimated by weighting equally across yearly cross-sectional means of β, where the yearly cross-sectional means are taken across all industries and markets present for the year. Standard errors are taken by bootstrapping years of data. ** denotes two-sided significance at the five percent level.

Variable	$\sigma(X)$	β
Size of Portfolio where News is From	1.00	1.31^{**}
		(0.13)
Volatility of News Generating Portfolio	0.45	0.27
		(0.17)
Industry Exports to Country where News is From	1.00	0.03
		(0.12)
Est. Corr. of Portfolio Ret. on Equity	1.00	0.10^{**}
		(0.04)
Common Language Dummy	0.49	-0.12
		(0.11)
Analyst Coverage Overlap Between Portfolios	0.22	5.24^{**}
		(0.40)
Cross-Border Equity Holdings Within Pair	1.00	0.81^{**}
		(0.15)
Industry Cross-Listings Within Pair	0.09	4.14^{**}
		(0.62)
Size of Responding Stocks	1.00	0.45^{**}
		(0.15)
Volatility of Responding Portfolio	0.52	3.46^{**}
		(0.30)
PRS Group Investment Risk Measure	1.00	0.03
		(0.11)
Adjacent Country Dummy	0.29	0.25
		(0.16)
Cultural Distance	1.00	-0.47^{**}
		(0.06)
Turnover of Responding Portfolio	1.00	-0.76^{**}
		(0.23)
Trading Hour Overlap	1.00	0.06
		(0.09)