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Is College a Focal Point of Investor Life?

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Abstract. We study the link between college interaction and portfolio choice. We consider both the general imprinting of values shared by all the students attending the same school—values-based interaction—and the ensuing interaction with the classmates—bonding-based interaction. We show that even after controlling for the standard motivations of portfolio theory, college-based interaction affects the choice of styles—growth/value investing as well as stock picking. Both dimensions of interaction—values-based and bonding-based interactions—contribute to shape the investor choice. Overall, college interaction significantly affects portfolio choice. Investors invest in the same stocks in which their former classmates do. Each individual college leaves a specific and distinct trace on his students.

JEL Classification: G11, G14

1. Introduction

One of the main tenets in finance is that portfolio choice is a function of the information of the investors. Investors have access to different pieces of information and, even if they share the same information, may interpret it differently (e.g., Kraus and Smith, 1989; Harris and Raviv, 1993). However, we know little about the process through which information is transmitted, elaborated, and aggregated.

One way information is transmitted is through social interaction. Human beings, by interacting with one another, transmit information and influence the way this information is elaborated. This phenomenon has been extensively studied in social sciences and in economics (e.g., Ellison and Fudenberg, 1995; McFadden and Train, 1996; Akerlof, 1997; Bala and Goyal, 1998; Bikhchandani, Hirshleifer, and Welch, 1998; Bertrand, Luttmer, and Mullainathan, 2000). More recently, Hong, Kubik, and Stein (2004) show that how social interaction—defined at the level of the community—affects the decision of investors to enter the stock market. The way information is elaborated and aggregated depends on the degree of similarity among investors. Similar investors interpret information in the same way (e.g., Barber, Odean, and Zhu, 2009).

One key source of social interaction is college. College experience is a precious source of social interaction. Attendance at the same college induces proximity among students and establishes and reinforces common views as well as creates long-lasting bonds by promoting social networks of classmates. College acts as a catalyst for individuals with similar aspirations in life as well as a forge of shared views and bonding.[1] More specifically, college-based interaction consists of both the general imprinting of values shared by all the students attending the same school and the ensuing interaction with the classmates. That is the establishment of bonds among people attending the same school at the same time that persists over time on a friendship or alumni basis. We will call the former values-based interaction and the latter bonding-based interaction.

Values-based interaction can be loosely interpreted as the interaction with the values of the school. It creates an overall view of the world—*Weltanschauung*—that is made of values, interests, and beliefs. These are inextricably linked and it is not clear that the investors are conscious of them. For example, it is possible that students attending MIT share a view of the world different from that of students of Harvard. The former group has a more technocratic view of the world, while a more generalist education in the school like Harvard provides a broader and more humanistic view of the world. In Scandinavia, the analogs of MIT are Royal Technical School (better known as KTH) and Chalmers Technical School, while Uppsala University probably would be analog of Harvard. However, this difference in views and preferences does not necessarily mean that the students from a specific school always have preferences for a specific type of stock. For example, it may be argued that investors coming from Harvard would not like defense stocks. However, the choice is way more complex as Harvard investors may have a preference for ethic stocks coupled with one related to the age at which they attended Harvard—value, capital intensive stocks. If investors attended Harvard before the time of the student revolution (1968) at a time of high patriotic feelings (Eisenhower presidency), defense stocks may actually be the preferred ones. It is therefore almost impossible to derive a unique relationship between school and type of stock. The analysis should be instead based on the link between preferences—whatever they are—of different investors that shared a common feature: school attendance.

[1] For example, Meier and Frey (2004) show that while more selfish students self-select into business study, business education further reinforces their natural traits.

Bonding-based interaction is the establishment of bonds among people attending the same school at the same time that persists over time on a friendship- or alumni basis[2].

Given that that college-based interaction is rooted in the past, the main question is how much of it survives over time and affects current choices. That is, do people who attended the same college have similar investment attitudes? The answer to this question may help to explain hitherto unexplained puzzles in the financial markets. Indeed, if college-based interaction matters and its impact is sizable, the behavior of financial markets may be more "predetermined" than we usually think of. That is, current market behavior may be related to the past school interaction of the investors. This implies that fads, bubbles, and investment waves may be explained in terms of a new cohort of investors coming to the market with a different view of the world and different network of friends.

The purpose of this paper is to tackle these issues. The analysis is empirical and based on a new and unique data set that allows us to inspect the individual components of an investor's overall portfolio and relate them to his nonfinancial income. This is, to our knowledge, the first paper to combine detailed individual portfolio holding data with comprehensive information on all the components of the nonfinancial wealth of the household as well as information about the investor's college education. The data set contains a representative sample of the Swedish population and has information on the wealth of the investors, broken down into their components (cash, equity holdings, real estate, loans, bonds, and other assets). We have detailed information at the investor level about the college he went to, the sociodemographic and economic conditions of the family at the time he went to college, his current profession, and his geographical location.

We borrow from the economic literature to construct tests of social interaction (Glaeser and Scheinkman, 2001, 2002; Glaeser, Scheinkman, and Sacerdote, 2003; Horst and Scheinkman, 2006). We show that the time spent at college affects the

[2] From conversation with alumni relation administrators, it seems that before 1990, there were only few colleges that were involved actively in maintaining alumni networks. After the banking crisis of early nineties, the election of a center-right government and adjustments in budgetary policies, practically all colleges and universities have become actively involved in alumni network building with the expressed purpose to solicit donations and create employment opportunities for both current students and alumni. The role of alumni network is increasing. University of Gothenburg states on its Web site that as "state funding decreases in importance, in common with other universities, the University of Gothenburg is becoming increasingly dependent on different contributors and foundations. Donations and gifts are consequently very important for large areas of research and development" (http://www.gu.se/english/research/donations/). Alumni networks of Swedish colleges are active both in Sweden and in abroad. KTH alumni network has active chapters as far as China.

future financial decisions of the investors in two ways: bonding-based interaction and college-based interaction. In the former case, the group within which the interaction takes place is represented by all the investors who went to the same school as the investor at the same time he attended it. In the case of values-based interaction, the reference group is represented by all the investors who ever went to the same school of the investor but not at the same time he attended it. College-based interaction differs from the mere effect of having the same level of (higher) education, which we will control for separately.

We start by providing evidence that college-based interaction generates differential investment behavior. On average, investors who attended the same college are more likely to hold a similar portfolio than investors who went to different colleges. Then, we focus on the choice between growth and value stocks and document that the decision to invest in growth stocks is related to the interaction of the investor with all the other investors belonging to the same group as well as to the objective characteristics and motives of the investor (i.e., desire to hedge the investor's nonfinancial income risk, amount of information available, financial and borrowing constraints) and to market conditions. We find strong evidence that college-based interaction affects portfolio choice. One standard deviation increase in college-based interaction results in investors increasing the fraction of growth stocks in their portfolios from 60 to 67% or by 12%.[3] If we look separately at the effect of bonding-based interaction and values-based interaction, we see that both of them have a positive and statistically significant impact. One standard deviation increase of bonding-based (values-based) interaction raises the fraction of growth stocks in the portfolio by 81% (22%). That is, investors tend to invest in growth stocks if their former classmates do the same.

Next, we consider the decision to invest in a particular stock. We show that college interaction is positively related to stock picking. One standard deviation increase in the intensity of the college interaction for some stock results in an increase in the percentage of the portfolio invested in the stock from 49.6 to 64.4% or by about 30% of the dependent variable's mean. Both bonding-based and values-based interactions are separately significant. One standard deviation increase of bonding-based interaction increases the fraction of the specific stock in the investor portfolio from 47 to 57% or by 21%. One standard deviation increase of values-based interaction makes the investor increases the fraction of the specific stock in his portfolio from 47 to 48.5% or by 3%.

[3] We compute the economic magnitude in the following way. A one standard deviation increase in X changes the dependent variable Y (e.g., fraction invested in growth stocks) by an amount equivalent to (mean(Y) + std(X) $\times$ β)/mean(Y), where β is the regression coefficient.

Then, we focus on the individual colleges. We individually and jointly consider the top fifteen colleges and five main communities. We uncover evidence of college-specific effects for each of the top fifteen colleges. The average value of own-college effect (other-college effect) is 0.462 (0.006). This is distinct and separate from community-specific effects. We also show that college-specific interactions affect the investor semiannual portfolio rebalancing.

Finally, we consider the relation between college-based interaction and performance. Is interaction just a behavioral bias that destroys value or a way through which less-informed investors cope with their lower information relying on word-of-mouth information transmitted by their peers? We find evidence of the latter one. We document that the more closely the investor mirrors his college portfolio, the higher is his Sharpe ratio. This is robust across specifications, and it is also economically significant. In particular, investors who have their portfolios closer to that of their colleges by one standard deviation enjoy a Sharpe ratio 0.12 higher than average (from the mean of 0.43–0.55). This result supports the view that college-based interaction far from being a bias that destroys value, does actually provide useful information that helps the investor.

Overall, these findings suggest that college-based interaction has a long-lasting effect on investor behavior. This takes the form of both creation of common values that last over time—values-based interaction—and continuous exchange of interaction in the future—bonding-based interaction. Both determine the investment behavior, affecting portfolio choice. Investors tend to invest in the same stocks in which their former classmates do. The positive relationship with performance suggests that there is an informational component that is most likely related to bonding-based interaction.

It is worth noting that we cannot fully reject the possibility that part of the effect of college-based interaction is just a reflection of long-term societal structure—parental influence affecting admission in most prestigious schools. While we have reasons to believe that meritocratic admission system based on Swedish SAT test (Högskoleprovet) limited the direct effects of such skewed admission, still it cannot totally eliminate the indirect effects via family attitudes toward education, time and money available for extracurricular activities, etc. It is also important to note that this criticism is not applicable to the results on bonding-based interaction.

Recently, Grinblatt, Linnainmaa, and Keloharju (2010) showed that high IQ investors outperformed low IQ ones. It is possible that some of the results for values-based interaction for highly selective schools (KTH, Karolinska Institute, and Stockholm School of Economics) are driven by IQ among other factors. But it is hard to explain the superior performance of investors who more closely mimics his college portfolio, nor is it possible to explain bonding-based interaction.

Also, it is important to note that we are not necessarily talking about political preferences. Generally, in Sweden, higher education is mostly public with a few notable exceptions[4]. The education is very secular. Religious or political values do not percolate into the education process at university level. For example, Berggren, Jordahl, and Stern (2009) did not find any evidence on systematic left–right divide among social scientists at university level in Sweden. Even more important, as was shown by Bourdieu (1988), the divide right–left cuts across disciplines. For example, in Swedish, Business Administration professors tend to be 3-to-1 to the right, while in Sociology, the ratio is 5:1 to the left. Unfortunately, we do not have similar data for hard sciences for Sweden. It is possible that students self-select into area of studies based on their political beliefs (Meier and Frey, 2004). However, it should not affect the results at university level. One notable exception is Stockholm School of Economics that concentrates on Economics and Business Administration.

Our findings have different implications. First, they complement the literature dealing with the effects of "proximity investment" (or familiarity). Investors are shown to invest in the stocks of companies headquartered close to where they live (Coval and Moskowitz, 1999, 2001; Huberman, 2001). Our measures of college interaction not only are robust to the inclusion of proxies for proximity investment but they also dwarf them in explanatory power.

These results also induce us to suggest a normative implication related to the relationship between education and college-based interaction. If education affects investors' choice in relation to what the investors learned at college, a change in the quality of education may have profound implications in terms of future stock market behavior. If, however, what really affects investors' choice is the social interaction taking place at school—college-based interaction—then the type of education will matter less and the cross-interaction between students will make all the difference. In the former case, governmental policies for education may affect future investor behavior, while in the latter case, these policies are mostly neutral. Our findings provide a first step in the direction of distinguishing the two components of college-based interaction. However, many issues are still unresolved and open to discussion.

The paper is structured as follows. In the next section, we describe the data and the construction of the main control variables. In Section 2, we provide data

[4] There are only three private schools in the country. Among top fifteen educational institutions, we are looking at in details below there are only two of those schools: Chalmers Technical School (became private in 1994 only, in the very end of our sample) and Stockholm School of Economics. Private schools obey by the same admission and graduation rules as the public universities; however, they have more flexibility on research side. For the purposes of our study, the differences between private and public educational institutions are insignificant.

description. In Sections 3, 4, and 5, we provide the main results. In Section 6, we discuss the results. A brief conclusion follows.

2. Data and Construction of the Variables

2.1 DATA SOURCES

We use different sources. For each investor, we have detailed information of his individual holdings of stocks (broken down at the stock level), bank accounts, real estate, and other types of wealth. Fiscal authorities provide us with information on the different forms of investor income as well as demographic and family characteristics. This information is matched at the individual level, so as to construct a time series of investment and income for each investor. For each stock, we have detailed information on the company and the price, volume, and volatility at which it trades. We now explain the data in detail.

Individual stockholding

We use the data on individual shareholders collected by Vardepapperscentralen, the Security Register Center. The data contain both stockholding held directly and indirectly through a financial company or brokerage, including holdings of US-listed ADRs. In addition, SIS Ägarservice AB collects information on ultimate owners of shares held via trusts, foreign holding companies, and the like (for details, see Sundin and Sundqvist, 2002). Our data cover the period 1995 through 2000. Overall, the records provide information about the owners of 98% of the market capitalization of publicly traded Swedish companies. For the median firm, we have information about 97.9% of the equity, and in the worst case, we have information on 81.6% of market capitalization of the firm. The data provided by SIS Ägarservice AB were linked by Statistics Sweden with the LINDA data set described below.

LINDA

LINDA (Longitudinal INdividualDAta for Sweden) is a register-based longitudinal data set and is a joint endeavor between the Department of Economics at Uppsala University, the National Social Insurance Board (RFV), Statistics Sweden, and the Ministries of Finance and Labor. It consists of a large representative panel of households for the population over the period 1960–2000. For each year, information on all family members of the sampled individuals is added to the data set. The sampling procedure ensures that the data are representative for each year. Moreover, the same family is traced over time. This provides a real time series dimension that lacks in surveys based on different cohorts polled over time.

The variables include individual characteristics (gender, age, marital status, country of birth, citizenship, year of immigration, place of residence detailed at the parish level, education, profession, and employment status), housing information (type and size of housing, owner, rental and occupation status, one-family or several-family dwelling, year of construction, and housing taxation value), and tax and wealth information. In particular, the income and wealth tax registers include information on labor income, capital gains and losses, business income and losses, pension contributions, taxes paid, and taxable wealth. A description is provided by Edin and Fredriksson (2000) and is available at linda.nek.uu.se.

For the purposes of this paper, we compute the current market value of housing using the tax-assessed value provided by LINDA. We evaluate it at current prices by using the average ratio of market value to tax-assessed value that is provided for each year and county by the Swedish Office of Statistics. There is no estimate of the market value of privately held companies. However, the database contains an indicator variable for owners of privately held companies and entrepreneurs who file their business tax returns along with their personal tax returns. For the privately held unlimited-liability companies, the value of the assets is included in the tax return. For the privately held unlimited-liability companies that are not listed, the value of assets held is generally missing. However, the size of the group is rather small (1.74–1.91% of the sample depending on year) and is unlikely to affect our estimates in a significant way. Moreover, for the members of the wealthiest 5,000 families, we reconstructed their values using information from SIS Ägarservice AB (Sundin and Sundqvist, 2002).

The combined LINDA/Shareholding data set covers the period 1995–2000. The overall sample we use contains 1,757,406 observations. In addition, we also use 1990–1994 data from LINDA in the implementation of the Carroll and Samwick (1997) procedure to construct the moments of conditional nonfinancial income we describe below. In Table I, we report some descriptive statistics. Panel A contains the general demographic characteristics (number of household members, age, income and wealth composition, etc.) and descriptive statistics for variables defined, while Panel B reports graduation year distribution.

College data

For 25,500 investors, part of 18,663 households, we have information about the colleges they attended. In addition, for each college, we have information about the enrollment, average GPA, location, and ranking on a nation-wide basis. There

Table I. Descriptive statistics

This table contains the descriptive statistics of the sample. Panel A reports the general demographic characteristics. We report yearly nonfinancial income, risky assets, bank deposits, residential real estate, debt, household size, and age of oldest member of the household and ability. Ability is based on the difference between an individual's income and the average income of his profession normalized by the standard deviation of income in the profession. For a subset of households, we also define the heritage variables, that is, the decile of capital or labor income of the parental household at the time the investor was 10 years old or in 1970 (whichever is later). College interaction is defined as the average fraction of the portfolio allocated to a given firm (in excess of weight of the firm in the Swedish market portfolio) among all investors who attended college *c*. We define geographical interaction as all the investors living in the same community out of the 289 Swedish communities. We define as professional factor, the set of investors who work for the same industry. We define as education factor the set of investors who attained the same education level. We define these variables at the individual stock level (where the variable on an individual level is the fraction of the stock in excess of its weight in the market portfolio) and at the level of the growth stocks in the portfolio (where the individual variable is the fraction of the portfolio allocated to one-third of the companies with highest market-to-book ratio). In the case of concentration, we construct the average value of the degree of portfolio concentration of the investors that either live in the same area or attended the same college or attained the same education degree. Geographical proximity is the logarithm of the inverse of the distance between the ZIP code of the investor and the ZIP code of the closest branch/subsidiary of the company whose stock we consider. The measures of correlation are calculated using the Carroll and Samwick (1997) methodology. Panel B reports the distribution of the sample over the graduation years. Unless noted otherwise, all monetary values are in thousands of Swedish Kronor (SEK).

Panel A: general demographic characteristics of households

Variable	Mean	Median	Standard deviation
Nonfinancial income	623	531	798
Risky assets	2,690	437	17,840
Bank deposits	478	146	1,290
Real estate	844	699	766
Debt	985	402	2,277
Household size	3.415	4	1.318
Age	43.369	44	6.873
Ability	0.119	0.072	0.574
Heritage variable (labor income decile)	6.28	8	3.107
Heritage variable (capital income decile)	5.195	6	3.303
Corr(nonfinancial income, stock returns)	−0.030	0.000	0.393
Corr(nonfinancial income, real estate)	−0.091	−0.013	0.471
Stockholding-based measures			
College interaction	−0.013	−0.001	0.059
Geographical interaction	−0.003	0.001	0.049
Professional factor	−0.008	−0.001	0.032
Education factor	−0.009	−0.001	0.023
Geographic proximity	−4.557	−5.022	1.202
Diversification-based measures			
College interaction	0.828	0.823	0.185
Geographical interaction	0.813	0.796	0.220

Continued

Table I. Continued

Professional factor	0.815	0.844	0.120
Education factor	0.825	0.874	0.108
Panel B: graduation date distribution			

Graduation date	% of the sample
Before 1980	20.26
1981–1985	24.64
1986–1990	18.40
1991–1994	15.96
After 1995	20.74

are 102 colleges. However, we use only 54, as for the 48 smallest ones, the sample was too small[5]. Moreover, we have background information about the parental household ("heritage variables"), such as wealth and income, at the time of their childhood.[6]

Other data

For individual security returns (including dividends) and the overall market index (SIX market index), we use the SIX Trust Database. It provides dividend- and capital changes-adjusted returns for all Scandinavian-listed stocks. For information on firm-level characteristics, we use the Market Manager (MM) Partners Databases. It contains information on income statements and balance sheets of all limited-liabilities firms in Sweden. The information is collected from annual reports and mandatory filings with Swedish Tax Authorities. MM also contain information at the plant level, including municipality location and ZIP code of the plant. These two databases are the equivalent of, respectively, CRSP and COMPUSTAT for the USA. Geographical coordinates are from the Swedish Postal Service and contain latitude and longitude of Swedish post offices.

2.2 CONSTRUCTION OF THE MAIN CONTROL VARIABLES

Testing for social interaction is complicated by the confounding effect of other factors, such as wealth, status, and family characteristics. For example, it is possible that students who attended the Stockholm University have similar patterns of investment behavior simply because they come from wealthier families than students attending a local liberal arts college. Moreover, even if they came from-families with analogous economic characteristics, the task of identifying college-

[5] For example, we dropped the Ballet School, the Institute of Drama, the Opera Institute, and the like. The typical yearly intake in these schools is of the order of just fifteen to twenty-five students.
[6] All income variables are measured when college attendee was 10 years old or in 1970 (whichever is later).

specific effects could be thwarted by the difference in wealth, income, profession, and status of the investors at the time when their investment actually takes place. We therefore try to account for the alternative factors affecting investor behavior—namely, hedging nonfinancial income risk, familiarity, momentum, wealth, and demographic and heritage factors. We now consider these in detail.

Nonfinancial risk variables

A first set of variables deals with investors' nonfinancial income exposure. They capture the investor's level of nonfinancial income, its volatility and the correlation between the investor's financial and nonfinancial income, and the correlation between the latter and the investor's real-estate income. We consider nonfinancial income as the sum of labor and entrepreneurial income. We construct measures of the permanent (expected) nonfinancial income following the approach of Carroll and Samwick (1997) and Vissing-Jorgensen (2002). We refer to them for a more detailed description. We also include variables that account for the investor speculative motive. To control for momentum trading and feedback trading strategies, we include the return and volatility of the stock in the previous 12 months.

Measures of familiarity

We consider measures that act as a proxy for the degree of familiarity of the investor with a stock. Familiarity has been identified as a key factor affecting the investor decision to hold a stock (Coval and Moskowitz, 1999, 2001). This may be due to a behavioral bias (Huberman, 2001) as well as to limited information (Merton, 1987; Shapiro, 2002).

Our measure of familiarity is based on geographical proximity—the proximity between the residence of the investor and the place where the company is located. We consider two different measures: the first one is the logarithm of the inverse of the distance between the ZIP code of the investor and the ZIP code of the closest branch/subsidiary of the company whose stock we consider. As an alternative measure, we use the logarithm of the inverse of the distance between the ZIP code of the investor and the ZIP code of the company headquarters. Given that the results do not differ and the variables are highly collinear, we report only the first specification. These measures are analogous to those proposed by Coval and Moskowitz (1999, 2001) in a study of geographical preferences in mutual fund investment. The greater the value of the variable, the closer the investor is to the stock. These measures are constructed at the stock level and then aggregated at the investor level, across all the stocks of his portfolio, weighted by their share in the portfolio.

To control for the fact that investors are also interacting with other investors geographically located close to them, we add a variable defined as "geographical factor." This is constructed as the fraction of the stocks held on average by the other investors who live in the same municipality—"community." Furthermore, to control for the fact that investors are also interacting with their colleagues in the same profession, we add a variable defined as "professional factor." This is constructed as the fraction of the stocks held on average by the other investors who work for the same industry. The professions are defined based on the SNI92 industrial classification as reported by LINDA.

Measures of wealth and other control variables

The measures of wealth include the financial and real-estate wealth. We also use the ratio of investor debt to total assets. The demographic variables include household size, the age of the oldest member of the family of the investor, and its value squared. This latter variable is consistent with standard results (Guiso and Jappelli, 2002; Vissing-Jorgensen, 2002) that find a nonlinear relationship between age and the degree of stock market participation. Furthermore, we construct a variable to act as a proxy for the ability of the investor in his occupation. This is based on the difference between his income and the average income of his profession. The assumption is that the higher the income of the investor relative to the average income of the other investors in the same area, the higher his ability should be.

Education

The general level of education may play a role. For example, it is possible that high school dropouts invest differently from people with university diplomas. This might reflect the level of intellectual development as well as differences in culture and worldview (on top of income differential). To control for this, we add a variable that controls for the effect of sharing the same level of education. This variable is constructed analogously to the other measures of interaction, but the group is made up of the other investors who earned college degrees. We will call this variable "education factor." Moreover, for each college, we build variables based on the parental income (capital and labor based on monetary value and decile of distribution) and geographic and gender distribution of the student body.

Another important issue is whether the college merely a proxy for field of study or major. Suppose, for example, that a particular university is an engineering school. Graduates may end up buying a lot of the same stocks just because of their common interest in engineering and not because of any social interactions. To control for this issue, we construct a series of dummies (education specialization) that account for the field of study of major.

3. Preliminary Evidence

We start by gathering evidence on whether college-based interaction generates differential investment behavior. We focus on the portfolio composition of investors attending different colleges. We construct portfolios that replicate the average portfolio of the investors who attended the same college and then we test whether there is any statistical difference between them. For each individual i, stock j, and college c, we proceed as follows. First, we group the stocks on the basis of book-to-market, size beta, and liquidity.[7] For each classification, we consider three subgroups: low, medium, and high (i.e., bottom 33%, intermediate 33%, and top 33%). Second, for each college, we trace the investors who attended it and are present in our data set in 1995. For each of them, we identify their portfolio holdings and the fraction of their portfolios represented by each stock. This gives us the percentage investment (defined as fraction of the portfolio of the investor) of the ith investor who attended the cth college and invested in the jth stock.

Finally, for each college, we calculate the average percentage investment in each subgroup of stocks of the investors who attended the college. This is done for each pair stock/college. For example, we determine the average percentage investment in low book-to-market stocks of the Uppsala University by aggregating the percentage investment in low book-to-market stocks of all the investors who went to the Uppsala University. The same procedure is repeated for the years 1996, 1997, 1998, 1999, and 2000. This generates, for each college, six yearly time series of average percentage investments. These represent the "college portfolios," that is, they mimic the "investment behavior" of the colleges. We then test whether these time series differ. We apply the Kruskal–Wallis test, the median one-way test, the Van der Waerden one-way test, and the Savage one-way test.

The results are reported in Table II. All the tests agree and provide very strong statistical evidence supporting the existence of college-based investment styles. On average, investors who attended the same college are more likely to hold a similar portfolio than investors who went to different colleges. This analysis, though suggestive, still does not directly quantify the impact of social interaction. This is the goal of the next section.

[7] As a proxy of liquidity, we use the ratio of bid-ask spread to price. Beta is estimated by Capital Asset Pricing Model (CAPM) regression on 52 weeks returns.

Table II. Differences in portfolio allocations due to college-based interaction

This table reports the results of mean and median tests of the differences of the portfolios holdings by alumni of different colleges. For each individual i, stock j, and college c, we proceed as follows. First, we group the stocks into classes based on book-to-market, size, beta, and liquidity. Second, for each college, we trace the investors who attended it and are present in our data set in 1995. For each of them, we identify their portfolio holdings and the fraction of their portfolios represented by each stock. This gives us the percentage investment (defined as fraction of the portfolio of the investor) of the ith investor who attended the cth college and invested in the jth stock. Then, for each stock classification (i.e., book-to-market, size, beta, and liquidity), we consider three subgroups: low, medium, and high (i.e., bottom 33%, intermediate 33%, and top 33%). Finally, for each college, we calculate the average percentage investment in each subgroup of stocks of the investors who attended the college. The same procedure is repeated for the years 1995, 1996, 1997, 1998, 1999, and 2000. The tests are performed on the differences between portfolios. As a proxy of liquidity, we use the ratio of bid-ask spread to price. Beta is determined by running CAPM style regression using 52 weeks of returns. Portfolio composition is measured in the end of the month of December. We report the corresponding statistics and the p values.

	Mean test		Kruskal–Wallis test		Median one-way test		Van der Waerden one-way test		Savage one-way test	
Portfolios	F	Pr > F	χ^2	Pr > χ^2	χ^2	Pr > χ^2	χ^2	Pr > χ^2	χ^2	Pr > χ^2
Small size	1.75	0.0030	67.00	0.0035	67.83	0.0029	63.76	0.0074	68.40	0.0025
Medium size	2.26	<0.0001	88.93	<0.0001	84.15	<0.0001	91.65	<0.0001	87.45	<0.0001
Large size	1.31	0.0950	69.05	0.0021	68.25	0.0026	67.21	0.0033	68.73	0.0023
Low market-to-book	2.47	<0.0001	97.46	<0.0001	89.12	<0.0001	92.19	<0.0001	95.26	<0.0001
Medium market-to-book	2.03	0.0001	84.16	<0.0001	80.16	0.0002	83.08	<0.0001	82.70	<0.0001
High market-to-book	1.82	0.0012	81.33	0.0001	85.67	<0.0001	74.70	0.0007	84.16	<0.0001
Low liquidity	1.42	0.0475	57.26	0.0297	45.92	0.2074	54.78	0.0481	57.96	0.0258
Medium liquidity	2.25	<0.0001	89.87	<0.0001	94.51	<0.0001	83.72	<0.0001	93.61	<0.0001
High liquidity	1.55	0.0158	77.15	0.0003	75.80	0.0004	76.11	0.0003	76.60	0.0003
Small beta	2.20	<0.0001	89.11	<0.0001	83.86	<0.0001	86.08	<0.0001	87.49	<0.0001
Medium beta	1.68	0.0047	72.82	0.0012	76.57	0.0004	71.67	0.0015	76.99	0.0004
Large beta	1.87	0.0008	81.42	0.0001	81.06	0.0001	84.12	<0.0001	81.43	0.0001

4. Social Interaction and Portfolio Choice

4.1. A FIRST TEST

We first test whether there is evidence of college-based interaction. Let us assume there are $i = 1{:}v{:}I$ investors who belong to a particular network (e.g., they went to the same school) and may take an action A. The action can be, for example, the actual choice of an asset. The literature (Glaeser and Scheinkman, 2001, 2002; Glaeser, Scheinkman, and Sacerdote, 2003; Horst and Scheinkman, 2006) models the impact of social interaction as follows:

$$A_i = \alpha + \beta X_i + \gamma N_i + \theta_i, \tag{1}$$

where A_i is the action of the ith investor, while N_i represents the action of the other investors belonging to ith investor's group. The action is affected by observable action- and individual-specific characteristics (X_i) and by the actions of all the other individuals belonging to the same group (N_i). The term X_i reflects the role of the exogenous determinants of the level of the action. θ_i is a stochastic term that proxies for individual unobservable characteristics.

For example, A_i represents the fraction of the portfolio of the ith investor that is invested in growth stocks in excess of the market portfolio. The decision to (over)-invest in growth stocks is a function of the observable (X_i) and unobservable (θ_i) characteristics of the stock and of the social network interaction to which the investor belongs (N_i). Our goal is to assess the impact of the social network (i.e., γ). College-based interaction is defined in terms of the investors who attended the same college. We also control for geographical interaction, where the group is represented by the municipality where the investor lives.

We start by considering the choice between growth and value stocks, so that the dependent variable is the fraction of growth stocks in the portfolio of the investor. Growth stocks are defined, each period, as the top 33% of the companies by market-to-book ratio. The decision to invest in growth stocks is related to the interaction of the investor with all the other investors belonging to the same group and to the investor's characteristics and motives (e.g., desire to hedge the investor's nonfinancial income risk) and to market conditions.

We consider different specifications. The base specification contains a constant, the level of wealth of the investor (aggregate financial and real-estate wealth), his level of debt (i.e., loans), the education factor, and demographic variables, such as a variable that proxies for the individual abilities of the members of the household (ability), the number of adults in the household (18 year and older), the size of the family (i.e., the number of members in the household), and the age and the square of the age of oldest member of the household. The second specification also includes the hedging variables. These are the mean and volatility of the nonfinancial income and its correlation to the stock returns and to investor's real-estate income. The different moments of nonfinancial income have been constructed according to the Carroll and Samwick (1997) and Vissing-Jorgensen (2002) methodology. In the Appendix, we describe the instrumental and Heckman methodology we employ.

The results are reported in Table III. We consider different specifications: the first set—Specifications 1 and 2—are simple ordinary least square (OLS), while the rest—Specifications 3–6—are instrumental variables specifications. In Panel A, we consider the overall college-based interaction, while in Panel B, we split college-based interaction into bonding-based interaction and values-based interaction. The findings show that social interaction affects the choice to skew the portfolio toward growth stocks. Indeed, any type of social interaction increases the incentive to invest in growth stocks. The economic magnitude is relevant: one

Table III. College-based interaction and portfolio choice: growth investing

This table reports the estimates of the demand of investors for growth stocks (defined as the fraction of stock portfolio of individual investors invested in high market-to-book stocks) as a function of the measures of social interaction (college-based and geographical interactions) and the control variables. In Panel A, we consider the overall college-based interaction. The base specification contains a constant, the level of wealth of the investor (aggregate financial and real-estate wealth), his level of debt (i.e., loans), the education and professional factors and demographic variables, such as a variable that proxies for the individual abilities of the members of the household (ability), the number of adults in the household (18 year and older), the size of the family (i.e., the number of members in the household), the age and the square of the age of oldest member of the household. Specifications 2 and 3 adds Heckman's λ. Specification 4 also includes the hedging variables. These are the mean and volatility of the nonfinancial income and its correlation to the stock returns and to investor's real-estate income. The different moments of nonfinancial income (i.e., aggregate labor and entrepreneurial income) have been constructed according to the Carroll and Samwick (1997) and Vissing-Jorgensen (2002) methodology as defined in the text and in the Appendix. We use different levels of clustering. In Specifications 1–4, we cluster over household and in Specifications 5 and 6 over college and commune correspondingly. Specifications 1 and 2 are estimated using OLSs, while estimates in Specifications 3–6 are based on an instrumental variable methodology. We use as instruments college characteristics (average capital income, average decile of capital income, and gender composition of the student body) and regional variables (local tax rate, number of banks in locality, population density, percent of foreign-born and welfare-using population, and distance from airport). We report statistics of the quality of the instruments. These are the F test and the p value of the first stage in the instrumental estimation as well as the F test and the p value of the test on excluding the instruments in the first stage of the instrumental estimation. First-stage results are presented in the Table AI. We report also the adjusted R^2 and the p value of the Hansen test of overidentifying restrictions. The measures of social interaction are defined in the text. The estimates are based on 23,928 observations. In Panel B, we split college-based interaction into bonding-based interaction and values-based interaction. Specifications 1–4 are similar to Specifications 3–6 in Panel A correspondingly.

Panel A: Base Estimate: college-based interaction

	(1)		(2)		(3)		(4)		(5)		(6)	
	Estimate	*t* Statistic	Estimate	*t* Statistic	Estimate	*t* Statistic	Estimate	*t* Statistic	Estimate	*t* Statistic	Estimate	*t* Statistic
College-based interaction	0.346	9.39	0.412	11.34	0.626	4.48	0.624	4.46	0.758	4.96	0.695	5.88
Geographical interaction	0.272	10.47	0.256	10.79	−0.033	−0.23	−0.033	−0.23	−0.040	−0.35	−0.112	−0.78
Control variables												
Wealth	−0.135	−16.45	−0.064	−7.10	−0.066	−8.11	−0.063	−7.75	−0.065	−7.95	−0.059	−9.28
Debt	−0.000	−0.16	−0.002	−1.21	−0.001	−0.70	−0.001	−0.75	−0.001	−0.44	−0.002	−1.31
Ability	0.008	1.81	0.007	1.69	0.003	0.69	0.001	0.12	−0.006	−1.58	0.000	−0.12
Size of household	0.026	9.16	0.025	8.92	0.028	9.83	0.027	9.44	0.024	12.37	0.026	9.00
Age	0.011	3.09	−0.005	−1.27	−0.011	−3.72	−0.011	−3.95	−0.009	−3.14	−0.011	−5.67
Age^2	−0.010	−2.90	0.006	1.53	0.012	4.02	0.012	4.22	0.010	3.43	0.013	5.86

Parental labor income decile	0.002	1.55	0.002	1.50	0.003	1.93	0.003	1.92	0.000	0.30	0.002	1.56
Parental capital income decile	−0.002	−1.54	−0.002	−1.19	−0.002	−1.57	−0.002	−1.50	−0.001	−0.83	−0.001	−1.07
Nonfinancial income (level)							0.003	0.47	0.000	−0.02	0.007	1.71
Nonfinancial income (volatility)							−0.014	−2.96	−0.013	−4.09	−0.018	−3.46
Corr(nonfinancial income, portfolio returns)							0.006	0.75	0.003	0.48	0.010	1.38
Corr(nonfinancial income, real estate)							−0.003	−0.37	−0.005	−0.74	−0.001	−0.16
Education factor	−1.535	−9.45	−1.568	−9.74	−1.597	−9.68	−0.171	−1.39	−0.111	−0.78	−0.259	−2.26
Professional factor	−0.124	−1.03	−0.165	−1.19	−0.174	−1.41	−1.602	−9.70	−1.679	−11.12	−1.544	−11.32
Intercept	1.007	9.28	0.708	6.37	0.871	8.77	0.880	8.81	0.804	6.99	0.862	10.01
Heckman's λ			0.136	15.73	0.151	15.24	0.156	15.54	0.148	16.43	0.157	19.71
Adjusted R^2	0.149		0.167									
					J statistic	*p*	*J* statistic	*p*	*J* statistic	*p*	*J* statistic	*p*
Hansen's statistics					13.783	0.055	13.844	0.054	13.509	0.061	6.570	0.475
Time dummies	Y		Y		Y		Y		Y			Y
Clustering	Household		Household		Household		Household		College		Commun	

	Dependent variables							
Diagnostics of first stage of instrumental regression	College-based interaction	Geographical interaction	College-based interaction	Geographical interaction	College-based interaction	Geographical interaction	College-based interaction	Geographical interaction
F statistic of first stage	1006.16	454.43	862.91	390.45	862.91	390.45	862.91	390.45
p Value of the first stage	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F test of excluded instruments	223.96	79.26	222.93	79.10	222.93	79.10	222.93	79.10
p Value of the test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Panel B: values-based and bonding-based interactions

	(1)		(2)		(3)		(4)	
	Estimate	*t* Statistic	Estimate	*t* Statistic	Estimate	*t* Statistic	Estimate	*t* Statistic
Values-based interaction	1.276	2.29	1.369	2.39	1.655	3.44	1.245	2.60
Bonding-based interaction	0.479	2.40	0.450	2.21	0.462	2.27	0.582	3.12
Geographical interaction	−0.113	−0.64	−0.102	−0.57	−0.220	−1.71	−0.118	−0.66
Control variables								
Wealth	−0.064	−6.77	−0.061	−6.39	−0.066	−7.32	−0.056	−7.48
Debt	−0.001	−0.97	−0.002	−1.04	−0.001	−0.44	−0.002	−1.51
Ability	−0.002	−0.40	−0.007	−1.36	−0.011	−2.23	−0.009	−1.96
Size of household	0.028	8.35	0.026	7.75	0.025	9.23	0.026	7.27
Age	−0.018	−4.81	−0.019	−5.01	−0.019	−6.40	−0.018	−7.30
Age^2	0.018	4.86	0.019	5.02	0.018	6.16	0.018	7.57
Parental labor income decile	0.001	0.60	0.001	0.56	−0.001	−0.45	0.000	−0.04
Parental capital income decile	−0.003	−1.83	−0.003	−1.79	−0.003	−2.21	−0.002	−1.57
Nonfinancial income (level)			0.001	0.10	0.005	0.83	0.003	0.50
Nonfinancial income (volatility)			−0.024	−3.90	−0.024	−7.80	−0.024	−4.45
Corr(nonfinancial income, portfolio returns)			0.015	1.64	0.021	2.66	0.021	2.50
Corr(nonfinancial income, real estate)			−0.004	−0.52	−0.009	−1.26	−0.006	−0.71
Education factor	−0.230	−1.64	−0.237	−1.67	−0.116	−0.73	−0.263	−2.05
Professional factor	−1.554	−7.88	−1.541	−7.75	−1.660	−10.25	−1.548	−9.83
Intercept	1.158	7.90	1.188	7.94	1.273	9.15	1.094	7.98
Heckman's λ	0.155	12.61	0.161	12.71	0.155	19.35	0.160	16.00

	J statistic	*p*		*J* statistic	*p*			*J* statistic	*p*		*J* statistic	*p*
Hansen's statistics	8.098	0.324		7.672	0.362			10.851	0.145		4.812	0.683
Time dummies		Y			Y			Y			Y	
Clustering		Household			Household			College			Commun	
	Dependent variables											
Diagnostics of first stage of instrumental regression	Values-based interaction	Bonding-based interaction	Geographical interaction	Values-based interaction	Bonding-based interaction	Geographical interaction	Values-based interaction	Bonding-based interaction	Geographical interaction	Values-based interaction	Bonding-based interaction	Geographical interaction
F statistic of first stage	13.41	456.37	343.55	862.91	393.84	297.11	862.91	393.84	297.11	862.91	393.84	297.11
p Value of the first stage	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F test of excluded instruments	15.98	66.39	54.25	15.39	66.12	54.30	15.39	66.12	54.30	15.39	66.12	54.30
p Value of the test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

standard deviation increase in college-based interaction results in investors increasing the fraction of growth stocks in their portfolios from 60 to 67% or by 12%.[8] Geographical interaction has a small and mostly insignificant impact. Professional interaction, however, has a comparable impact: one standard deviation increase in professional interaction induces the investors to increase the fraction of growth stocks in their portfolios from 60 to 69% or by 14.5%. If we look separately at the effect of bonding-based interaction and values-based interaction, we see that both of them have a positive and statistically significant impact. It is worth comparing the economic magnitude. One standard deviation increase of bonding-based (values-based) interaction raises the fraction of growth stocks in the portfolio by 81% (22%).

It is important to notice that our measures of social interaction not only are robust to the inclusion of proxies for proximity investment but they also dwarf them in terms of explanatory power. This suggests proximity can be defined not only between the investors and the stock but also among investors themselves. Investors tend to invest in growth stocks if people who attended the same school invest in growth stocks. Given that the sample covers a period of stock market expansion, this suggests that social interaction induces investors to concentrate in the most "trendy" stocks.

4.2 A GENERALIZED PORTFOLIO CHOICE

We now focus on the decision to invest in a particular stock. We consider the *i*th investor, who attended the *c*th college, lives in the *k*th community, and invests in the *j*th stock. To keep notation simple, we omit the index for the stock. We customize Equation (1) so that the dependent variable is the fraction of the portfolio of the *i*th investor that is invested in the specific stock in excess of the allocation the investor would be holding according to CAPM. This way of defining the dependent variable partially controls for the speculative motive or the "Merton proportion" in a dynamic setting.[9] We estimate the following:

$$h_{i,c,k} = \alpha + \beta X_{i,c,k} + \gamma N_{i,c,k} + \kappa\lambda + \theta_{i,c,k}, \tag{2}$$

where $h_{i,c,k}$ is the fraction of the portfolio of the *i*th investor that is invested in the specific stock in excess of the allocation the investor would be holding according to CAPM. We use the same specification as before. With a slight abuse of notation, we use $X_{i,c,k}$ to represent the vector of all the control variables, the investor specific

[8] The result for OLS regression (Specification 2) is similar in magnitude. One standard deviation increase in college-based interaction makes investors raise the fraction of growth stocks in their portfolios from 60 to 65% or by 8%.

[9] The inclusion of past stock returns and volatility controls for momentum on trend-chasing strategies.

(e.g., demographic variables), the stock specific (e.g., stock volatility and momentum), and the other generic ones (e.g., time dummies). The set of control variables is augmented by stock-specific characteristics, such as the return and volatility of the stock in the previous 12 months (useful to capture trend- and momentum-chasing effects), the stock bid-ask spread, dividend yield, market-to-book ratio, and market capitalization (size). We also include the proxy for geographical familiarity.

The results are reported in Table IV, Panels A and B. We consider alternative specifications and different clustering (over household, over college, and over community). Panel A reports the overall specification, while Panel B breaks down college-based interaction into bonding-based and values-based interactions. The first two estimates are OLS, while the others are instrumental variable ones[10]. The results show some important points. First, college interaction is positively related to stock picking. These results hold across different specifications. More important, the results are robust to the inclusion of variables proxying for familiarity (Specifications 4–6). That is, college interaction is not a mere proxy for the standard familiarity biases identified in the literature. One standard deviation increase in the intensity of the college interaction for some stock results in an increase in the stock fraction and in investor's portfolio from 49.6 to 64.4% or by about 30% of the dependent variable's mean. This holds across different specifications and is robust to the inclusion of variables proxying for geographical proximity as well as geographic and professional factors.

Moreover, it is worth noting the separate explanatory power of bonding-based interaction. It is positive and strongly statistically significant. This holds across different specifications and, as before, is robust to the inclusion of variables proxying for geographic, professional, and holding-based proximity. The economic significance is high. One standard deviation increase of bonding-based interaction raises the fraction of the specific stock in the investor portfolio from 47 to 57% or by 21%. One standard deviation increase of values-based interaction makes the investor increase the stake in the specific stock from 47 to 48.5% or by 3%.

It would be interesting to see if there is a time series effect in college-based interaction—for example, whether the college effect degrades over time. However, we face a restriction in terms of the length of our sample. A proper test would require us to compare the same cohort of graduates over long period of time. With just 6 years of data, we cannot perform the test in a statistically meaningful way. Even worse, with this type of data, we would not be able to differentiate a "cohort" lifecycle effect from a diminishing interaction effect due to the college effect.

[10] We use as instruments college characteristics (average capital income, average decile of capital income, and gender composition of the student body) and regional variables (local tax rate, number of banks in locality, population density, percent of foreign-born and welfare-using population, and distance from airport).

Table IV. College-based interaction and portfolio choice: stock picking

This table reports the estimates of the demand of the investors for risky assets (defined as the fraction of stock portfolio of individual investors in excess of the market portfolio weights) as a function of the measures of social interaction and the control variables. In Panel A, the base specification contains a constant, the level of wealth of the investor (aggregate financial and real-estate wealth), his level of debt (i.e., loans), the education factor and demographic variables, such as a variable that proxies for the individual abilities of the members of the household (ability), the number of adults in the household (18 year and older), the size of the family (i.e., the number of members in the household), the age and the square of the age of oldest member of the household. The second and third specifications also include Heckman's λ stock characteristics. The fourth specification includes the hedging variables and stock characteristics. Hedging variables are the mean and volatility of the nonfinancial income and its correlation to the stock returns and to investor's real-estate income. The different moments of nonfinancial income (i.e., aggregate labor and entrepreneurial income) have been constructed according to the Carroll and Samwick (1997) and Vissing-Jorgensen (2002) methodology as defined in the text and in the Appendix. It also adds the geographical familiarity variable. We used different levels of clustering. In Specifications 1–4, we cluster over household and in Specifications 5 and 6 over college and commune correspondingly. In Panel A, Specifications 1 and 2 are estimated using cluster-adjusted OLSs, while all other specifications are based on an instrumental variable methodology. We use as instruments college characteristics (average capital income, average decile of capital income, and gender composition of the student body) and regional variables (local tax rate, number of banks in locality, population density, percent of foreign-born and welfare-using population, and distance from airport). We report the statistics on the quality of the instruments (in Panels A and B). In Panel A, we consider the overall college-based interaction, while in Panel B, we split college-based interaction into bonding-based interaction and values-based interaction. Specifications 1–4 are the same as Specifications 3–6 in Panel A. The estimates are based on 56,348 observations. We report also the adjusted R^2 and the p value of the Hansen test of overidentifying restrictions. The measures of social interaction are defined in the text.

Panel A: Stock holdings: college-based interaction

	(1)		(2)		(3)		(4)		(5)		(6)	
	Estimate	t Statistic	Estimate	t Statistic	Estimate	t Statistic	Estimate	t Statistic	Estimate	t Statistic	Estimate	t Statistic
College-based interaction	0.328	7.66	0.349	8.08	3.199	3.14	2.629	2.77	3.570	1.99	2.891	3.70
Geographical interaction	0.531	11.43	0.550	11.96	0.546	1.01	0.314	0.59	0.499	1.29	0.260	0.77
Control variables												
Return (previous 12 months)							0.003	2.19	0.004	3.64	0.003	2.85
Risk							−0.314	−7.96	−0.335	−6.37	−0.296	−8.50
Bid-ask spread							−0.039	−3.10	−0.040	−4.67	−0.043	−3.75
Size							0.054	16.74	0.053	14.84	0.056	16.25

Market-to-book ratio							0.000	1.71	0.000	0.84	0.000	0.93
Dividend yield							0.000	−1.08	0.000	−1.16	0.000	−1.47
High-tech dummy							0.020	3.34	0.023	2.49	0.019	2.83
Wealth	−0.301	−11.81	−0.110	−14.87	−0.117	−15.34	−0.111	−15.01	−0.121	−14.31	−0.114	−16.68
Debt	0.005	6.22	0.003	2.18	0.005	3.05	0.004	2.38	0.006	3.99	0.004	3.36
Ability	0.012	2.56	0.014	3.80	0.014	3.64	0.010	2.74	0.014	4.77	0.009	2.25
Size of household	0.047	13.80	0.030	10.50	0.032	10.44	0.031	10.66	0.031	11.41	0.030	10.53
Age	0.019	7.36	0.016	7.41	0.015	6.41	0.017	7.50	0.018	8.66	0.017	9.04
Age^2	−0.016	−6.25	−0.013	−5.79	−0.011	−4.56	−0.013	−5.71	−0.014	−6.56	−0.013	−6.74
Parental labor income decile	0.005	2.70	0.003	2.12	0.003	2.32	0.004	2.67	0.003	2.69	0.004	2.63
Parental capital income decile	−0.004	−1.93	−0.001	−0.91	−0.001	−0.91	−0.002	−1.06	−0.001	−0.70	−0.001	−1.13
Nonfinancial income (level)							0.008	1.64	0.005	1.41	0.006	1.46
Nonfinancial income (volatility)							−0.004	−0.96	−0.003	−0.69	−0.004	−0.85
Corr(nonfinancial income, stock returns)							0.004	0.63	0.005	0.95	0.002	0.39
Corr(nonfinancial income, real estate)							−0.026	−3.48	−0.032	−4.91	−0.028	−4.42
Geographic proximity							0.008	4.03	0.008	4.27	0.009	3.27
Professional factor	0.250	2.82	0.109	1.30	−0.548	−2.01	−0.351	−1.42	−0.670	−1.75	−0.417	−2.07
Education factor	−1.311	−10.38	−1.595	−13.18	−3.313	−4.87	−1.036	−1.55	−1.460	−1.55	−1.038	−1.63
Intercept	1.567	23.88	0.322	4.97	0.396	5.90	−0.283	−3.73	−0.288	−4.47	−0.287	−4.51
Heckman's λ			0.313	42.85	0.317	44.14	0.343	49.89	0.334	39.34	0.340	50.33
Adjusted R^2	0.253		0.339									
					J statistic	*p*	*J* statistic	*p*	*J* statistic	*p*	*J* statistic	*p*
Hansen's statistics					10.689	0.153	8.989	0.254	8.480	0.292	7.710	0.358
Time dummies	Y		Y		Y		Y		Y		Y	
Clustering	Household		Household		Household		Household		College		Commun	

Diagnostics of first stage	Dependent variables							
	College-based interaction.	Geographical interaction	College-based interaction	Geographical interaction	College-based interaction	Geographical interaction	College-based interaction	Geographical interaction
F statistic of first stage	372.51	861.55	260.68	602.97	260.68	602.97	260.68	602.97
p Value of the first stage	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F test of excluded instruments	30.60	177.92	31.21	178.62	31.21	178.62	31.21	178.62
p Value of the test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Panel B: Stock holdings: college-based and bonding-based interactions

	(1)		(2)		(3)		(4)	
	Estimate	t Statistic	Estimate	t Statistic	Estimate	t Statistic	Estimate	t Statistic
Values-based interaction	0.437	3.56	0.380	3.36	0.443	3.99	0.333	3.46
Bonding-based interaction	0.335	3.53	0.293	3.51	0.322	3.76	0.282	4.31
Geographical interaction	0.167	0.27	0.967	1.72	0.832	1.59	0.759	1.71
Control variables								
Return (previous 12 months)			0.005	2.28	0.008	4.03	0.005	2.83
Risk			−0.348	−6.17	−0.390	−8.15	−0.345	−5.96
Bid-ask spread			−0.058	−3.75	−0.056	−4.83	−0.048	−4.00
Size			0.058	10.04	0.056	10.77	0.061	11.72
Market-to-book ratio			0.001	1.76	0.001	2.06	0.000	1.29
Dividend yield			0.000	−0.59	0.000	−0.39	0.000	−1.44
High-tech dummy			0.034	5.26	0.040	7.52	0.032	4.94
Wealth	−0.126	−13.31	−0.123	−13.46	−0.129	−14.41	−0.123	−20.28
Debt	0.002	1.04	0.001	0.78	0.002	1.60	0.001	0.62
Ability	0.009	2.07	0.006	1.30	0.006	1.74	0.006	1.62
Size of household	0.041	9.63	0.038	10.08	0.039	12.64	0.037	11.23
Age	0.017	6.41	0.018	7.53	0.019	9.55	0.016	7.43
Age^2	−0.014	−5.48	−0.016	−6.57	−0.016	−8.77	−0.014	−6.39
Parental labor income decile	0.002	0.92	0.002	1.26	0.002	1.26	0.002	1.24
Parental capital income decile	−0.002	−1.13	−0.002	−1.25	−0.002	−1.65	−0.002	−1.44
Nonfinancial income (level)			0.016	2.87	0.014	2.99	0.016	2.88

Nonfinancial income (volatility)				−0.011	−2.45			−0.013	−3.07		−0.012	−2.28
Corr(nonfinancial income, stock returns)				0.003	0.38			0.001	0.24		0.001	0.25
Corr(nonfinancial income, real estate)				−0.021	−2.50			−0.020	−2.71		−0.021	−3.09
Geographic proximity				0.012	5.03			0.012	5.46		0.015	6.71
Professional factor	0.261	2.00		0.185	1.55			0.155	1.54		0.171	2.27
Education factor	−1.154	−2.16		0.070	0.13			0.214	0.46		0.458	1.29
Intercept	0.496	5.50		−0.138	−1.34			−0.072	−0.76		−0.105	−1.05
Heckman's λ	0.358	22.72		0.386	25.86			0.386	23.61		0.380	28.22
	J statistic	p		J statistic	p			J statistic	p		J statistic	p
Hansen's statistics	2.564	0.922		5.647	0.582			6.630	0.468		5.931	0.548
Time dummies	Y			Y				Y			Y	
Clustering		Household			Household			College			Commun	
Diagnostics of first stage	Values-based interaction	Bonding-based interaction	Geographical interaction	Values-based interaction	Bonding-based interaction	Geographical interaction	Values-based interaction	Bonding-based interaction	Geographical interaction	Values-based interaction	Bonding-based interaction	Geographical interaction
F statistic of first stage	164.97	105.52	846.82	136.98	138.71	586.67	136.98	138.71	586.67	136.98	138.71	586.67
p Value of the first stage	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F test of excluded instruments	97.51	74.08	140.10	97.61	75.54	160.76	97.61	75.54	160.76	97.61	75.54	160.76

4.3 THE ROLE OF SPECIFIC COLLEGES

Can we say anything about the effect of the individual colleges or communities? We now consider an alternative specification that borrows from Hong, Kubik, and Stein (2005). We focus on the fifteen biggest (by number of students) colleges and five most populous geographical aggregations (counties, or län). The latter aggregates different communities. We estimate the following:

$$\begin{aligned} h_{i,c,k} =& \sum_c \alpha_c \{N_{i,c} \times I(a = c)\} + \sum_c \beta_c \{N_i \times I(a \neq c)\} \\ &+ \sum_k \alpha_k \{N_{i,k} \times I(l = k)\} + \sum_k \beta_k \{N_{i,k} \times I(l \neq k)\} \\ &+ \gamma N_{i,r} + \delta X_{i,c,k} + \kappa\lambda + \theta_{i,c,k}, \end{aligned} \quad (3)$$

where $h_{i,c,k}$ is the fraction of the portfolio that the investor i who attended college c and lives in the area k is investing in stock j. Let us use the indexes a and l to define, respectively, the college attended by the investor and the area in which he lives and use c and k to define, respectively, the other fourteen colleges and four areas. Then, $N_{i,c}$ ($N_{i,k}$) is the equally weighed average across all the investors who attended college c (live in the area k) of the fraction of the portfolio invested in stock j. The indicator $I(a = c)$ ($I(a \neq c)$) takes the value of 1 (0) if the cth college is the same as (different from) the one (ath) attended by the investor. Similarly, the indicator $I(l = k)$ ($I(l \neq k)$) takes the value of 1 (0) if the kth land is the same as (different from) the one (lth) in which the investor lives. The variable $N_{i,r}$ represents the behavior of all the other investors—that is, the ones who did not attend any of the fifteen colleges and/or live in any of the five areas. The other variables are defined as in the previous section.

The coefficients α_c and α_k can be interpreted as "own-college" and "own-community" effects, while the coefficients β_c and β_k represent the "other-college" and "other-community" effects. For example, let us consider the investment in H&M (i.e., j = H&M). If the investor i attended Lund University (i.e., a = Lund University) and lives in the area around Göteborg (i.e., l = Göteborg), then α_c captures how the decision to invest in H&M of the ith investor is affected by the average decision of the investors who attended Lund University and α_k captures how the decision to invest in H&M of the ith investor is affected by the average decision of the investors living close by (i.e., in Göteborg). The coefficient β_c captures how the decision to invest in H&M of the ith investor is affected by the average decision of the investors who attended the other fourteen main colleges or live in the other four main areas. For example, if c = Stockholm University, β_c proxies for the effect of the investors who attended Stockholm University. The γ captures the influence of the remaining colleges and areas. We expect that if the investor attended Lund

University, he will be more responsive to its average investment style than to that of other universities. Similarly, if such an investor lives in Göteborg, he will be more sensitivity to the average investment style of Göteborg than to that of the other areas.

The estimate of Equation (3) provides us with forty-one coefficients: fifteen for the "own-college" effect for each of the top fifteen colleges, fifteen for the "other-college" effect for each of the top fifteen colleges, five for the "own-community" effect for each of the top five areas, five for the "other-communities" effect for each of the other five areas, and an "other" effect for all the other colleges and communities. Also, to aggregate the coefficients to a single statistic, we calculate the weighted average of the α_cs and compare it to the weighted average of the β_cs. We then perform the same comparison for the α_ks and β_k. The weights are calculated using the number of investors in each group.

We report the results in Table V, Panel A. These findings provide additional evidence in favor of the role of the college interaction. The own-college effects are statistically significant and positive (although only ten of fifteen own-college effects are statistically significant)[11]. Other-college effects are either insignificant or negative. The average value of own-college effect (other-college effect) is 0.462 (0.006). The result of the F test of the coefficients comfortably rejects the hypothesis that own-college effect is equal either to other-college effect or to zero. At the same time, we fail to reject at 5% level, the hypotheses that all the other-college effects are equal and other-college effect is equal to own-college effect. We also do not find any evidence supporting community-based interaction. These results hold across different specifications and are robust to the inclusion to controls for riskiness of labor income.

We then consider a dynamic specification of Equation (3) by defining the trades as the semiannual change in holdings. As before, we estimate fifteen own-college effects for each of the top fifteen colleges, fifteen other-college effects for each of the top fifteen colleges, five own-community effects for each of the top five communities, five other-community effects for each of the other five communities, and one other effect for all the other colleges and communities. Also, we aggregate the coefficients into a single statistic by taking the weighted average of the α_cs and compare it to the weighted average of the β_cs.

We report the results in Table V, Panel B. The results are consistent with the previous findings and show that investors' trading is related to the trading of the other investors who went to the same college and live close by. In all the specifications, the own-college and own-community effects are strongly statistically significant, while the other-college and other-community effects are rarely

[11] The only exception is Specification 3, where one coefficient is negative, but not significant.

Table V. Stock holdings: individual college effect

In Panel A, we report the results of an OLS estimation (with white-corrected *t* statistics) of *j*s investor holdings (defined as share of company *i* in portfolio of investor who graduated from college *l* and lives in locality *k* from time $t-1$ to time *t* measured in prices of period $t-1$) on the average changes of portfolio choices of his college, of all other colleges, of his locality, and of all other localities: $h^i_{j,k,l,t} = \sum_c \alpha_c\{H^i_{c,t} \cdot I(l=c)\} + \sum_c \beta_c \{H^i_{xc,t} \cdot I(l \neq c)\} + \gamma H^i_{R,t} \sum_g \delta_g\{H^i_{g,t} \cdot I(k=g)\} + \sum_l \phi_l\{H^i_{xg,t} \cdot I(k \neq g)\} + \varphi H^i_{G,t} + \text{Controls} + \epsilon$, where $H^i_{c,t}(H^i_{g,t})$ is the equally weighted average (across investors) of the share of the portfolio that investors who graduated from college *c* (live in locality *k*) invest in stock *i* at time *t*. Similarly, $H^i_{xc,t}(H^i_{xg,t})$ is the average across all investors who did not graduate from college *c* (live in locality other than *k*). Finally, $H^i_{R,t}(H^i_{G,t})$ is the average calculated over all colleges (localities) that are not part of our focus group. Indicator variable $I(x)$ is equal to 1 if $x = 1$ and 0 otherwise. The controls are the same as in Table IV. We consider the top fifteen colleges and top five geographic locations as our focus group. We also report the tests of own-college/location versus other-college/location effects. Coefficients, γ,φ, and demographic, labor income, and stock characteristics control variables are omitted for brevity. We report coefficients for α_c and δ_c in column "Own-group effect" and coefficients for for β_c amd φ_c in column "Other-group effect." In Panel B, we report the results of the regression of the changes in *j*s investor holdings (defined as changes in share of company *i* in portfolio of an investor who graduated from college *l* and lives in locality *k* from time $t-1$ to time *t* measured in prices of period $t-1$) on the average portfolio changes of his college, all other colleges, his locality, and all other localities: $\Delta h^i_{j,k,l,t} = \sum_c \alpha_c\{\Delta H^i_{c,t} \cdot I(l=c)\} + \sum_c \beta_c\{\Delta H^i_{xc,t} \cdot I(l \neq c)\} + \gamma \Delta H^i_{R,t} + \sum_g \delta_g\{\Delta H^i_{g,t} \cdot I(k=g)\} + \sum_l \phi_l\{\Delta H^i_{xg,t} \cdot I(k \neq g)\} + \varphi \Delta H^i_{G,t} + \text{Controls} + \epsilon$, where $H^i_{c,t}(H^i_{g,t})$ is the equally weighted averages (across investors) of the share of the portfolio that investors who graduated from college *c* (live in locality *k*) invest in stock *i* at time *t*. Similarly, $H^i_{xc,t}(H^i_{xg,t})$ is the average across all investors who did not graduate from college *c* (live in locality other than *k*). Finally, $H^i_{R,t}(H^i_{G,t})$ is the average calculated over all colleges (localities) that are not part of our focus group. Indicator variable $I(x)$ is equal to 1 if $x = 1$ and 0 otherwise. Coefficients, γ,φ, and demographic, labor income, and stock characteristics control variables are omitted for brevity.

	(1)				(2)				(3)			
	Own-group effect		Other-group effect		Own-group effect		Other-group effect		Own-group effect		Other-group effect	
	Estimate	*t* Statistic	Estimate	*t* Statistic	Estimate	*t* Statistic	Estimate	*t* Statistic	Estimate	*t* Statistic	Estimate	*t* Statistic
Panel A												
Colleges												
Chalmers Technical School	0.101	1.00	−0.187	−2.62	0.100	0.60	−0.192	−2.78	0.213	1.11	−0.100	−0.73
Göteborg University	0.589	1.81	−0.004	−0.05	0.369	2.70	0.030	0.40	0.284	2.86	−0.202	−3.44

Continued

Table V. Continued

	(1)				(2)				(3)			
	Own-group effect		Other-group effect		Own-group effect		Other-group effect		Own-group effect		Other-group effect	
	Estimate	t Statistic	Estimate	t Statistic	Estimate	t Statistic	Estimate	t Statistic	Estimate	t Statistic	Estimate	t Statistic
Stockholm School of Economics	1.566	4.32	−0.220	−2.01	1.425	5.19	−0.209	−1.83	1.301	4.39	−0.259	−2.29
School of Health Sciences, Stockholm	0.727	2.71	−0.195	−0.90	0.827	3.45	−0.162	−0.82	0.394	1.01	−0.759	−4.28
Karolinska Institute	0.211	1.29	−0.099	−0.70	0.090	0.52	−0.005	−0.04	0.266	2.21	−0.191	−1.68
Royal Technical School (KTH)	0.534	2.05	0.047	0.48	0.323	1.12	0.027	0.27	0.253	0.77	−0.123	−1.32
Linköping University	0.308	2.22	0.052	0.51	0.406	2.60	0.057	0.60	0.300	2.51	−0.080	−0.90
Lund University	0.406	2.56	0.059	0.75	0.525	3.72	0.100	1.27	0.314	2.56	−0.127	−2.39
Stockholm Teaching School	0.266	1.13	0.046	0.55	0.034	0.13	0.057	0.67	0.153	0.41	−0.100	−1.06
Stockholm University	0.446	3.26	−0.008	−0.09	0.518	3.25	−0.037	−0.39	0.311	3.24	−0.207	−2.88
Swedish University of Agricultural Sciences	0.299	1.07	0.001	0.01	0.133	0.63	0.034	0.20	0.009	0.04	−0.325	−1.97
Umeå University	1.131	2.42	−0.041	−0.44	1.258	3.37	−0.005	−0.05	1.139	2.59	−0.101	−1.05
Uppsala University	0.486	2.63	0.061	0.63	0.494	3.87	0.096	0.91	0.369	3.16	−0.063	−0.62
Växjö University	0.174	0.38	0.160	0.66	0.105	0.27	0.192	0.77	−0.362	−0.88	0.027	0.09
College of Health Sciences in Göteborg	0.556	2.13	0.092	0.56	0.328	1.15	0.109	0.67	0.168	0.35	−0.013	−0.07
Geographic locations												
Stockholm	0.016	0.33	0.050	0.99	0.034	0.78	0.000	0.00	0.310	4.09	0.011	0.37
Uppsala	−0.023	−0.49	−0.018	−0.24	0.009	0.21	−0.041	−0.55	0.370	4.66	−0.090	−1.38
Södermanland	−0.027	−0.64	−0.023	−0.32	−0.007	−0.16	−0.041	−0.58	0.368	5.44	−0.140	−2.29
Göteborg	−0.041	−1.03	0.042	0.82	−0.059	−1.50	0.022	0.46	0.306	4.12	0.007	0.19
Lund	0.061	1.33	−0.014	−0.27	0.037	0.91	0.007	0.16	0.319	4.30	−0.040	−0.90
Demographic variables	Y				Y				Y			
Labor income variables	Y				Y				Y			
Stock characteristics	N				Y				Y			
Education specialization fixed effects	N				N				Y			
	F Statistic	p	F Statistic	p	F Statistic	p	F Statistic	p	F Statistic	p	F Statistic	p
All college effects = 0	4.41	0.000	1.56	0.084	5.51	0.000	1.56	0.084	8.39	0.000	2.64	0.001
All college effect equal	4.27	0.000	1.61	0.076	4.77	0.000	1.54	0.096	4.96	0.000	1.49	0.114
Own-college effect = other college effect	4.53	0.000			5.29	0.000			6.30	0.000		
All geographic effects = 0	1.42	0.216	0.51	0.768	2.19	0.055	0.25	0.941	6.31	0.000	1.68	0.155
All geographic effect equal	1.72	0.145	0.54	0.710	2.73	0.029	0.29	0.887	1.24	0.292	2.13	0.077

Continued

Table V. Continued

	(1)				(2)				(3)			
	Own-group effect		Other-group effect		Own-group effect		Other-group effect		Own-group effect		Other-group effect	
	Estimate	*t* Statistic	Estimate	*t* Statistic	Estimate	*t* Statistic	Estimate	*t* Statistic	Estimate	*t* Statistic	Estimate	*t* Statistic
Own geographic effect = other geographic effect	0.59	0.668			0.86	0.487			1.55	0.174		
Adjusted R^2	0.411				0.431				0.431			
Number of observations	56,348				56,348				56,348			
Panel B												
Colleges												
Chalmers Technical School	0.930	30.29	−0.290	−2.85	0.927	28.32	−0.268	−2.33	0.931	22.02	−0.265	−3.41
Göteborg University	0.830	30.05	−0.120	−1.84	0.842	28.16	−0.100	−1.37	0.840	19.70	−0.087	−1.86
Stockholm School of Economics	0.956	20.04	−0.198	−1.44	0.990	17.46	−0.183	−0.90	0.990	12.02	−0.201	−1.04
School of Health Sciences, Stockholm	0.920	26.18	−0.219	−1.95	0.932	24.34	−0.236	−1.79	0.934	16.49	−0.256	−1.81
Karolinska Institute	0.920	24.76	−0.217	−1.83	0.920	22.64	−0.185	−1.35	0.923	15.82	−0.195	−2.57
Royal Technical School (KTH)	0.926	34.18	−0.186	−2.49	0.920	31.01	−0.151	−1.76	0.921	25.47	−0.159	−2.00
Linköping University	0.803	27.46	−0.040	−0.52	0.812	25.83	−0.070	−0.79	0.816	16.81	−0.080	−1.22
Lund University	0.752	29.56	−0.052	−0.93	0.777	27.51	−0.050	−0.81	0.775	18.47	−0.050	−1.06
Stockholm Teaching School	0.900	31.49	−0.160	−1.89	0.896	28.02	−0.136	−1.44	0.899	21.16	−0.149	−1.98
Stockholm University	0.851	33.20	−0.161	−2.52	0.859	30.27	−0.155	−2.14	0.861	16.79	−0.166	−2.80
Swedish University of Agricultural Sciences	0.935	22.74	−0.194	−1.33	0.927	21.29	−0.138	−0.86	0.929	18.89	−0.138	−1.49
Umeå University	0.965	30.92	−0.156	−1.62	0.957	28.49	−0.144	−1.32	0.960	24.16	−0.131	−1.83
Uppsala University	0.812	29.54	−0.085	−1.19	0.825	27.77	−0.080	−1.00	0.828	18.00	−0.084	−1.56
Växjö University	0.977	25.41	−0.167	−1.17	0.987	24.01	−0.119	−0.76	0.989	19.99	−0.118	−1.82
College of Health Sciences in Göteborg	0.927	25.30	−0.202	−1.93	0.929	22.63	−0.192	−1.43	0.929	20.05	−0.191	−3.18
Geographic locations												
Stockholm	0.326	13.62	0.052	2.31	0.304	11.42	0.046	1.76	0.314	10.96	0.036	1.43
Uppsala	0.540	16.87	−0.098	−1.57	0.553	15.55	−0.115	−1.51	0.551	11.76	−0.111	−1.40
Södermanland	0.557	16.00	−0.143	−2.31	0.551	13.96	−0.205	−3.00	0.548	9.65	−0.195	−2.11
Göteborg	0.466	15.71	−0.052	−1.36	0.484	14.42	−0.102	−2.41	0.479	11.47	−0.087	−1.85
Lund	0.368	12.75	0.055	1.36	0.381	12.15	0.012	0.27	0.370	9.94	0.030	0.67
Demographic variables	Y				Y				Y			
Labor income variables	Y				Y				Y			
Stock characteristics	N				Y				Y			
Education specialization fixed effects	N				N				Y			
	F Statistic	*p*	*F* Statistic	*p*	*F* Statistic	*p*	*F* Statistic	*p*	*F* Statistic	*p*	*F* Statistic	*p*
All college effects = 0	616.50	0.000	2.44	0.002	523.50	0.000	1.45	0.122	316.59	0.000	2.49	0.001
All college effect equal	5.20	0.000	65.35	0.000	4.56	0.000	48.75	0.000	2.82	0.000	1.15	0.305
Own-college effect = other college effect	127.29	0.000			99.62	0.000			62.46	0.000		

Continued

Table V. Continued

	(1)				(2)				(3)			
	Own-group effect		Other-group effect		Own-group effect		Other-group effect		Own-group effect		Other-group effect	
All geographic effects = 0	184.96	0.000	3.98	0.001	152.83	0.000	4.48	0.000	99.85	0.000	2.77	0.017
All geographic effect equal	13.64	0.000	4.63	0.001	13.37	0.000	5.60	0.000	8.07	0.000	3.41	0.009
Own geographic effect = other geographic effect	57.54	0.000			52.40	0.000			22.76	0.000		
Adjusted R^2	0.370				0.375				0.375			
Number of observations	91,184				91,184				91,184			

significant and are smaller in absolute value. The average coefficient of own (other) college effect is 0.90 (−0.17).

5. Strength of Interaction and Performance

5.1 A VARIANCE-BASED TEST OF THE STRENGTH OF SOCIAL INTERACTION

We can now consider the percentage of the explained variance attributable to college interaction. We exploit the information contained in the variance of group averages. The intuition is that social interaction is "associated with large differences across time and space that cannot be fully justified by fundamentals" (Glaeser and Scheinkman, 2002, p. 361). We rely on the model of social interaction of Glaeser, Sacerdote, and Scheinkman (2003) that estimates the size of social interaction by using the relationship between the variance of group level aggregates and the variance of individual data. Glaeser and Scheinkman (2001) show that γ—that is, the sensitivity to the social network—can be estimated as follows:

$$\gamma = \frac{\mathrm{Var}_{\mathrm{agg}} - \mathrm{Var}_{\mathrm{ind}}}{\mathrm{Var}_{\mathrm{agg}} + \mathrm{Var}_{\mathrm{ind}}},$$

where $\mathrm{Var}_{\mathrm{ind}}$ is the variance of the choice variable (i.e., fraction of the portfolio invested in growth stocks) for the overall sample. $\mathrm{Var}_{\mathrm{agg}}$ is the variance of the difference between the average value of the choice variable for a group and the average of such a variable across the entire population. It is defined as variance of $\sqrt{N_c}(\bar{A}_c - EA)$, where $\bar{A}_c$ is the average value of the choice variable for all the investors who belong to group c, EA is the overall sample average, and N_c is number of investors who belong to group c. For example, for college c, the aggregate variance is $\sqrt{N_c}(\bar{A}_c - EA)$, where $\bar{A}_c$ is the average value of the choice variable over the graduates of college c, EA is the overall sample average, and N_c is the number of graduates of college c. The results of this specification are reported in Table VI, Panel A.

We also consider a second specification that controls for the other factors affecting portfolio choice as defined in the previous section. In this case, we have $EA = (\beta' X_c)/(1 - \gamma)$, where $\beta/(1 - \gamma)$ is estimated from a regression of $\bar{A}_c$ on the set of characteristics X for group c. That is, we estimate a regression of $\bar{A}_c$ on the set of variables Xs and use the predicted value from this regression to obtain a value of $\beta' \widehat{X}_c/(1 - \gamma)$. The control variables are college-based interaction. They comprise of average capital income of the parental family of the investors who attended the college, the average decile of capital income of the parental family, gender composition of the student body, and Stockholm dummy. The results are in Table VI, Panel B.

Table VI. Estimation of strength of social interaction

This table reports the estimation of the individual-level variance Var $B_{\mathrm{ind}B}$, the adjusted aggregate variance Var$B_{\mathrm{agg}B}$, and the parameter of strength of social interaction, $\gamma = (\mathrm{Var}B_{\mathrm{agg}B} - \mathrm{Var}B_{\mathrm{ind}B})/(\mathrm{Var}B_{\mathrm{agg}B} + \mathrm{Var}B_{\mathrm{ind}B})$. We estimate the parameters for the share of growth stocks in the stock portfolio (top 33.33% of the companies by market-to-book ratio). We report the results for both the overall sample and the year-by-year. In Panel A, the individual variance is the raw variance of variable of interest for overall sample. For the choice A (i.e., the fraction of the portfolio invested in growth stocks), the aggregate variance is defined as variance of $\sqrt{N_c}(\bar{A}_c - EA)$, where $\bar{A}_c$ is the average value of action A over the graduates of college c, EA is the overall sample average, and N_c is the number of graduates of college c. In Panel B, the individual variance is the variance of the variable of interest, controlling for college fixed effect. The aggregate variance is the variance of $\sqrt{N_c}(\bar{A}_c - \frac{\beta' X_c}{1-\gamma})$, where $\beta'/(1 - \gamma)$ is estimated from regression of $\bar{A}_c$ on the set of control variables (X) defined in Section 5 of the text.

	Individual variance	Aggregate variance	γ	Effect separated by 100
Panel A: unadjusted estimates				
Total	0.203	28.485	0.986	0.241
by Year				
1995	0.209	16.463	0.975	0.079
1996	0.212	17.368	0.976	0.087
1997	0.218	27.902	0.985	0.210
1998	0.212	26.952	0.984	0.208
1999	0.183	41.725	0.991	0.416
2000	0.182	36.638	0.990	0.371
Panel B: adjusted estimates				
Total	0.201	31.697	0.987	0.282
by Year				
1995	0.205	16.985	0.976	0.089
1996	0.208	20.763	0.980	0.135
1997	0.214	27.005	0.984	0.206
1998	0.209	18.077	0.977	0.099
1999	0.180	27.571	0.987	0.270
2000	0.182	56.673	0.994	0.526

We display the estimates of the individual-level variance ($\mathrm{Var}_{\mathrm{ind}}$), the adjusted aggregate variance ($\mathrm{Var}_{\mathrm{agg}}$), and the parameter of strength of social interaction (γ). We report the results both for the overall sample and year-by-year. The findings are in line with the previous results. They show that social interaction affects portfolio choice. In particular, γ—the estimate of the strength of the social interaction—is both economically and statistically significant, close to 1 and far from 0. The strength of the effect can be represented in terms of the correlation between decisions of two members of a social group who do not have direct contact with each other but are separated by other ninety-nine members of the group. The correlation between such investors is of the order of 25%. It is interesting to note that the strength of social interaction increases significantly in 1995–2000, reaching 40% in late nineties.

5.2 SOCIAL INTERACTION AND PERFORMANCE

Finally, we now focus on the effects that social interaction has on performance. For each investor, we construct the Sharpe ratio of his portfolio and relate it to the degree to which the investor is affected by the college interaction and to some other control variables. Each semester, we construct the Sharpe ratio of stock portfolio of stocks held by the investor by using returns in the period. We then define, for each investor, a measure of his sensitivity to social interaction. This is defined as $\mathrm{Diff}_i = \sum_{J=1}^{S} w_{i,j}|w_{i,j} - H_c^i|$, where $w_{i,j}$ is the fraction that the ith investor has invested in stock j, while H_c^i is the fraction of stock i in the portfolio of college c. Diff is negatively related to the impact of social interaction. The closer the investor's portfolio is to the one of his school—that is, the more exposed he is to college interaction—the lower this variable will be. Then, for each investor, we regress the Sharpe ratio on Diff and on a set of control variables.

We report the results in Table VII. We consider alternative specifications. In Specifications 1–3, we control for basic demographic characteristics. In Specification 4, we add the income-hedging variables. We start with OLS estimates with year fixed effects in Specification 1, adding Heckman's λ in Specification 2. In Specifications 3 and 4, we use Generalized Method of Moments (GMM) estimates. The instruments are age and parental labor and capital income deciles. Finally, in Specification 4, we add labor income variables and education specialization fixed effects.

The results show a strong negative statistical relation between Sharpe ratios and Diff. That is, the more similar the investor is to his college portfolio, the higher his Sharpe ratio. This suggests that college interaction being related to portfolio composition is also directly related to performance. This is robust across specifications, and it is also economically significant. In particular, investors who have their portfolios closer to that of their colleges by one standard deviation enjoy a Sharpe ratio 0.12 higher than average (from the mean of 0.43–0.55). The net effect is positive, inducing a higher net-of-risk performance. This result supports the view that college-based interaction far from being a bias that destroys value, does actually provide useful information that helps the investor.

In our performance analysis, we concentrate on the difference between "college portfolio" and individual portfolio. While it is possible that portfolios on both college and individual level are systematically different (in fact, Table II clearly states that "college portfolios" are different along M/B and size dimensions), the direction of those deviations is clearly beyond the scope of this paper.

6. Discussion

These results show that having attended the same college has a long-lasting effect on investor behavior. This is, to our knowledge, the first direct evidence in favor of

Table VII. Portfolio performance

We report the estimates of the determinants of Sharpe ratio. We define for each investor $\mathrm{Diff}_i = \Sigma_i w_i \mathrm{ABS}(w_{i,t} - H^i_{c,t})$ as portfolio share weighted average of absolute value of difference between college-wide average of portfolio share of stock i and individual share in the portfolio. In Specifications 1–3, we control for basic demographic characteristics. In Specification 4, we added income hedging variables and education specialization fixed effects. In Specification 2–4, we use Heckman selectivity correction. Estimates are clustered over household and used year fixed effects. Estimates in Specifications 3 and 4 are done using instrumental variables estimates. We use as instruments age and parental labor and capital income decile. We also report the result of the first-stage instrumental estimation (for Specification 4) and diagnostics of first stage in Specifications 3 and 4.

	(1)		(2)		(3)		(4)		First stage	
	Estimate	t Statistic	Estimate	t Statistic	Estimate	t Statistic	Estimate	t Statistic	Estimate	t Statistic
Diff	−0.373	−22.00	−0.261	−15.78	−0.434	−3.04	−0.421	−4.89		
Wealth	0.165	9.41	0.019	1.46	0.141	5.11	0.098	4.07	−0.029	−6.14
Debt	0.004	1.95	0.004	2.16	−0.005	−1.26	−0.003	−0.89	0.002	2.74
Ability	−0.037	−4.90	−0.036	−5.11	−0.027	−1.85	−0.019	−1.36	0.005	1.55
Size of household	−0.026	−6.92	−0.012	−3.44	0.003	0.38	0.003	0.35	0.022	15.75
Nonfinance income (level)							−0.023	−1.66	0.006	1.91
Nonfinance income (volatility)							−0.033	−2.70	−0.009	−3.42
Corr(nonfinance income, portfolio returns)							0.043	1.70	0.005	1.29
Corr(nonfinance income, real estate)							−0.025	−1.31	−0.013	−3.63
Age									0.003	16.88
Parental labor income decile									0.001	0.90
Parental capital income decile									−0.001	−2.11
Heckman's λ			−0.274	−19.69	−0.353	−7.33	−0.311	−6.14	0.151	30.56
Intercept	−0.224	−3.74	0.838	10.00	0.733	3.03	1.366	5.44	0.524	16.92
Adjusted R^2	0.150		0.191						0.109	
Number of observations	14,571		14,571		14,571		14,571		14,571	
					J statistic	p	J statistic	p		
Hansen's statistics					5.350	0.069	3.786	0.151		
Year fixed effects	Y		Y		Y		Y		Y	
Education specialization fixed effects	N		N		N		Y		Y	
Clustering	Household		Household		Household		Household		—	
Diagnostics of first stage					F statistic	p	F statistic	p		
F statistic of first stage					218.59	0.000	216.20	0.000		
F test of excluded instruments					108.42	0.000	55.96	0.000		

a form of social interaction that is related to college and it is different from education or type of degree. Moreover, unlike recent literature on social interaction (Hong, Kubik, and Stein, 2004), these findings directly relate social interaction not only to the decision to participate in the stock market but also to the portfolio allocation. This gives the first evidence on how social interaction affects the overall class of individual investors.

Given that college-based interaction is a form of interaction that is rooted back in the past, our findings have relevant implications for the process of price determination in the stock market. Indeed, current stock market behavior may be explainable in terms of past interactions. The very origin of a bubble may be related to different cohorts of investors coming to the market, each characterized in terms of the type of interaction they had at school and the social networks they developed there. Indeed, the main feature of a bubble is the divergence between the price of the stock and the fundamentals. One way of explaining this divergence is resorting to cascades. These are situations in which the choice of an investor is based on the information derived by observing the actions of other investors. Cascades make investors ignore their own information and rely on the uninformed choices of the previous investors (e.g., Bikhchandani, Hirshleifer, and Welch, 1998).

However, cascades do not originate at all times and, when they do, they differ in terms of their intensity and lasting. Part of this difference can be explained in terms of the process through which information is transmitted, elaborated, and aggregated. Social interaction makes it easier for investors to observe the actions of their peers. If a bubble is related to the fact that a new cohort of investors comes to the market with a new view of the world, the impact of the new cohort should be a function of the type of social interaction that characterizes it. The stronger the degree of social interaction, the more a cascade-type effect may arise. Our findings, by showing that one of the main factors affecting this process is social interaction, provide a first indirect link between word-of-mouth investing and the literature on bubbles. If college-based interaction matters and its impact is sizable, the behavior of financial markets may be more "predetermined" than we usually think of. That is, current market behavior may be related to the past school interaction of the investors.

7. Conclusions

We show that college interaction is related to portfolio choice. The magnitude is not only statistically significant but also economically relevant. Investors invest in the same stocks their former classmates do. We focus on the role of schools as providers of both education and bonding experience for the people attending them. Both of them seem to play a critical role.

Our findings are a first step toward the understanding of the way different forms of social interaction affect portfolio choice and the stock market. If investor choice is highly affected by the college years and especially by the type of interaction and bonding developed at the time, current stock prices may be explainable in terms of different cohorts of people coming to the market with different views of the world and information channels defined at an early stage of their life. Stock market bubbles and price anomalies can then be rationalized in terms of the type of generation coming to the market and the type of stocks listed or sold at the time.

Appendix: Econometric Issues

We now consider the econometric issues involved in the estimation of the main equations.

CORRELATED VARIABLE PROBLEM

One econometric problem is the presence of correlated error terms across individuals. Part of this problem is addressed by controlling for observable individual characteristics. The quality of the approach therefore depends on how important the unobservable characteristics are, these being the ones that induce correlations across individuals. In the ideal case in which X_i is independent within the group and independent of the social interaction term N_i, the estimation of Equation (1) would require only a simple OLS. However, omitted personal/group-specific characteristics may be correlated with N_i. The bias may be due to the fact that investors who attended a particular school tend to invest more in a stock for their own specific—and not properly controlled for—reasons. This would induce a spurious correlation between portfolio choice and investor-specific characteristics.

To address this issue, we estimate Equation (1) using an instrumental variable methodology with an expanded set of control variables. We use two sets of instruments. The first is an average set of characteristics of the school at the time the investor attended it. These are the characteristics of the people who attended the college recorded at the time they attended the college (averaged across all the people who attended it) such as the capital income of the parental family of the investors who attended the college, the decile of capital income of the parental family, and the gender composition of the student body. We argue that these variables are related to the quality (and selectivity) of the school and that it is more likely that in higher quality schools, the effect of both selectivity and educational imprinting is larger. For example, the average portfolio choice of the graduates of the University of Stockholm can be explained in terms of the average income of their parental families at the time they went to college. We therefore project our average college variable that proxies for interaction—for example, excess holdings of stocks—on the set of characteristics of the investors at the time they joined the college. Given that we directly control for the parental income of the ith investor at the time he went to college among the explanatory variables, the parental income of his classmates should not, in the absence of college interaction, explain the choice of the ith investor today through any other way than through the indirect effect of social interaction between classmates. The second set of instruments is related to geographical and local variables (local tax rate, number of banks in locality, population density, percent of foreign-born and welfare-using population, and distance from airport).

To assess the quality of our instruments, we report diagnostic statistics. We report the F statistics and their p values of the first stage in the instrumental variable regression as well as the Hansen statistics of the test of overidentification for the second stage.[12] In all the specifications, the diagnostics show that the instruments are strongly statistically correlated with the endogenous proxy of interest and do not affect the dependent variable of interest through a channel other than their effect via the endogenous explanatory variables. We also augment our control variables with variables that may affect portfolio choice by indirectly influencing the choice of either college or locality. The inclusion of all these variables helps to reduce the presence of correlated error terms across individuals due to unobserved individual characteristics (Manski, 1993).

At the second stage, we also include an extensive number of control variables (X_i) that account for the other factors affecting investor demand that may aggregate at the group level and induce correlation within-group and between-group average characteristics and individual behavior. These factors are related to the other determinants of portfolio choice, such as hedging, speculation, and momentum investing; familiarity and borrowing constraints; as well as other demographic, geographic, and professional factors affecting investor behavior. They are defined in the data section.

It may be the case that the characteristics of an individual that would lead him to attend a school (e.g., high parental income) may be correlated with the same characteristics that induce other investors to attend the same college. This may induce spurious correlation if this individual characteristic were omitted at the second stage. We therefore include these characteristics (e.g., high parental income) among the control variables in the main regression. Finally, we also include among the controls a "geographic factor" that proxies for the interaction of people who live in the same area. We instrument it using instruments that explain the average community investment choice.

[12] The full-fledged set of instruments is reported in the heading of the tables. We regress the residuals of the second stage on the instruments. The results (not reported) show no residual correlation.

SELF-SELECTION PROBLEM

The econometric estimation of Equation (1) has to account for the selection bias due to the fact that the participation in stock market decision is endogenous. To address this issue, we use a two-stage procedure of Heckman (1979) and separately estimate the decision to enter the stock market and the portfolio choice. The decision to enter the market can be represented as follows:

$$P_i = \alpha + \beta X_i^p + \gamma N_i + \eta_i, \tag{A1}$$

where P_i is a dummy that takes the value of 1 if the investor participates in the financial market and 0 otherwise, while X_i^p is a vector of control variables. X_i^p differs from X_i in terms of some variables that provide the identification restriction in the Heckman specification.[13] N_i is defined as the fraction of investors who participate in the stock markets who either live nearby (i.e., in the same community) or attended the same college. The probability of entering the financial market is modeled as a normal cumulative density function. Given that Equation (A1) is just an auxiliary regression needed only for the proper estimation of the second stage, for brevity, we will not discuss it. However, the main results are reported in Table AI. From Equation (A1), we derive λ_{it} that is employed in the second stage to control for the selection bias.

CROSS-CORRELATION ISSUES

We have to estimate panel structure in the presence of potentially correlated errors across individuals and across time. Various approaches have been adopted to address this issue (panel with individual and/or time fixed effect, purely cross-sectional estimates, Fama and MacBeth cross-sectional, and time series approach). The fact that the residuals are correlated across observations makes the OLS standard errors biased and underestimates the true variability of the coefficients. In the case of both individual and time effects, it can be shown that the best avenue is to address one parametrically (e.g., including time dummies) and then estimate standard errors clustered on the other dimension (Petersen, 2009). We therefore adopt as our approach a panel specification with time fixed effect and clustering at household level. We also experiment with time effect and clustering along the dimension of social interaction (community or college). We use GMM with robust variance–covariance matrix. We employ data disaggregated at the individual investor level.

[13] X_i^p also contains time dummies, macroregions, industry dummies, and the correlations between nonfinancial income and the market portfolio contains the prior 12-month returns and volatility of the investor's portfolio, his prior capital gains and losses separately considered, and his tax rate.

Table A1. First-stage regression for college, values, bonding, and geographic-based interactionThis table reports the first-stage regression for Specification 4 in Table III, Panel A, and Specification 2 in Table III, Panel B, as defined in the Appendix. The variables are defined as in the previous tables. All the estimates are multiplied by 100, except density and college capital income that are multiplied by 100,000.

	College-based interaction		Values-based interaction		Bonding-based interaction		Geographical interaction	
	Estimate	*t* Statistics	Estimate	*t* Statistics	Estimate	*t* Statistics	Estimate	*t* Statistics
Wealth	−1.132	−6.90	−0.102	−0.63	−0.900	−3.60	0.169	0.58
Debt	−0.018	−0.65	−0.016	−0.61	0.015	0.37	−0.058	−1.22
Ability	−0.010	−0.10	−0.006	−0.06	0.060	0.36	−0.434	−2.27
Size of household	−0.038	−0.76	0.034	0.68	−0.091	−1.20	0.133	1.51
Age	0.178	3.67	0.181	3.64	−0.141	−1.84	−0.393	−4.42
Age^2	−0.189	−3.89	−0.137	−2.79	0.077	1.01	0.376	4.29
Parental labor income decile	−0.016	−0.72	−0.002	−0.09	−0.032	−0.90	0.051	1.25
Parental capital income decile	0.005	0.22	0.029	1.18	−0.017	−0.46	−0.029	−0.68
Nonfinancial income (level)	0.042	0.35	0.200	1.55	−0.074	−0.37	0.197	0.86
Nonfinancial income (volatility)	−0.174	−1.79	0.280	2.90	−0.416	−2.81	−0.613	−3.57
Corr(nonfinancial income, portfolio returns)	−0.113	−0.69	−0.245	−1.52	0.023	0.09	0.201	0.70
Corr(nonfinancial income, real estate)	−0.192	−1.46	0.001	0.01	0.038	0.19	−0.142	−0.63
Education factor	1.452	0.38	−2.150	−0.57	3.046	0.52	−8.832	−1.31
Professional factor	−0.644	−0.24	2.672	1.02	−2.228	−0.55	−2.532	−0.54
College capital income	0.401	2.75	1.280	8.99	−0.923	−4.20	0.141	0.55
College capital income decile	−2.383	−25.39	−0.118	−1.29	−2.321	−16.46	−0.178	−1.09
College gender	21.626	31.12	8.882	4.58	−0.187	−0.06	−0.751	−0.22
Local tax rate	−0.093	−3.56	0.002	0.09	−0.072	−1.84	−0.232	−5.12
Number of banks in commune	−0.002	−0.73	0.001	0.61	−0.005	−1.35	−0.023	−5.21
Commune population density	0.030	2.06	−0.008	−0.57	0.043	1.94	0.174	6.80
% of foreign-born population	2.631	0.79	3.283	1.00	0.812	0.16	28.604	4.91
% of welfare recipient	6.170	1.90	−3.610	−1.14	9.663	1.98	−13.138	−2.32
Distance to the airport	0.254	4.76	−0.031	−0.60	0.235	2.92	1.496	16.02
Heckman's λ	−0.928	−4.56	−0.612	−3.08	0.044	0.14	2.657	7.50
Intercept	45.383	30.47	−5.808	−3.76	53.347	22.45	41.002	14.91
Adjusted R^2	0.638		0.130		0.506		0.426	

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