Socioeconomic Status and Macroeconomic Expectations*

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Abstract

We show that individuals' macroeconomic expectations are influenced by their socioeconomic status (SES). People with higher income or higher education are more optimistic about future macroeconomic developments, including business conditions, the national unemployment rate, and stock market returns. The spread in beliefs between high- and low-SES individuals diminishes significantly during recessions. A comparison with professional forecasters and historical data reveals that the beliefs wedge reflects excessive pessimism on the part of low-SES individuals. SES-driven expectations help explain why higher-SES individuals are more inclined to invest in the stock market and more likely to consider purchasing homes, durable goods, or cars.

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1 Introduction

Individuals' choices of consumption, saving, and investment depend on expectations about future macroeconomic conditions. As Mankiw, Reis, and Wolfers (2003), Souleles (2004), Puri and Robinson (2007), Dominitz and Manski (2007) and others have shown, there is substantial disagreement between individuals in their forecasts. Such heterogeneity can have important effects on asset prices and macroeconomic dynamics (e.g., Sims (2008), Geanakoplos (2009), Piazzesi and Schneider (2012), Guzman and Stiglitz (2015)). Consumption and investment choices induced by differences in beliefs further may have welfare consequences (Brunnermeier, Simsek, and Xiong (2014)). Yet the origins of this disagreement are still not well understood.

In this paper, we show that heterogeneity in macroeconomic expectations is associated with individuals' socioeconomic status (SES), measured by income and education. Our empirical analysis is motivated by experimental evidence. Kuhnen and Miu (2017) find that experimental subjects coming from low-SES backgrounds are more pessimistic about the payoff distributions of risky assets relative to high-SES subjects. Moreover, this gap in expectations between low and high-SES individuals' beliefs arises after good news about the payoff distribution is revealed in the experiment, but not after bad news. We build on this experimental work by analyzing the relationship between people's SES and their degree of optimism about the macroeconomy, as well as the dynamics of beliefs over the business cycle. We use monthly data spanning almost four decades from the Michigan Survey of Consumers (MSC).

We start by examining SES-related unconditional heterogeneity in expectations regarding future stock market returns, the national unemployment rate, and general business conditions. We find that within virtually every month during our almost four-decade sample, for each one of those expectations measures, and for both income rank within year-age groups and education as SES measures, high-SES respondents in the survey are more optimistic than low-SES respondents. These differences in beliefs are substantial, even after controlling for other demographic characteristics, age effects, and time fixed effects. For example, moving from the bottom to the top income quintile implies a change in macroeconomic optimism that is about the same magnitude as a third of a typical peak-to-trough movement over the business cycle in the monthly average beliefs in the Michigan Survey. Having a college degree corresponds to a belief difference of about 6% of a typical peak-to-trough movement.

We then turn to the business-cycle dynamics of the beliefs wedge between high and low-SES people. We show that the wedge is pro-cyclical. During recessions the macroeconomic expectations of high and low-SES individuals are quite similar, but the wedge widens substantially in times of good macroeconomic performance. Thus, there is a remarkable consistency in the behavior of the beliefs wedge in our long sample of survey data and in the experimental evidence that motivates our analysis.

As in the experimental data in Kuhnen and Miu (2017), we find that high-SES individuals make forecasts that are, on average, closer to an objective forecast than low-SES individuals. We test this implication by comparing the macroeconomic expectations from the MSC with matched forecasts from the Survey of Professional Forecasters (SPF) and, for beliefs about future stock returns in the MSC, with long-run historical realizations of stock market index returns. Based on these proxies for objective forecasts, we find that forecasts of high-SES individuals are, indeed, less biased based than those of low-SES individuals.

Having established the basic facts about the unconditional and the dynamic properties of SES-related heterogeneity in macroeconomic expectations, we examine in more detail the mechanism that leads to the correlation between SES and macroeconomic beliefs. A potential alternative theory to our baseline hypothesis of a causal effect of SES on macroeconomic expectations is that there is an underlying fixed personal characteristic—e.g., vulnerability to depression—that causes both general pessimism as well as poor economic choices that lead to low SES (see, e.g., Puri and Robinson (2007)). Relatedly, one could worry about reverse causality where pessimism causes economic choices that subsequently lead to low SES. However, using the panel sub-sample of the MSC in which respondents are re-interviewed once after six months we can difference out unobserved fixed personal characteristics. Doing so, we still find a strong positive relationship between *changes* in income and *changes* in macroeconomic optimism. These differenced results also make clear that a reverse causality story is unlikely to explain our results because a potentially plausible effect of beliefs changes on SES changes would take much longer than a few months to materialize. Furthermore, using the full MSC sample, we find that respondents who report a recent positive change in their personal financial situation or receipt of good economic news, as well as those who reside in geographic areas with positive recent changes in economic conditions have more optimistic macroeconomic beliefs. These proxies for experienced changes absorb part of the explanatory power of the SES level variables. Taken together, all of these results indicate that macroeconomic beliefs are responsive to recent changes in individuals' perceived economic circumstances, which does not fit well with fixed effects or reverse causality stories.

As a final step in our analysis, we show that differences in beliefs associated with individuals' socioeconomic standing help explain their economic behavior. Since the MSC offers data on beliefs about macroeconomic conditions, as well as information about respondents' actual or intended choices, such as stock market investment decisions and attitudes towards purchasing homes, durables or cars, we can quantify the effect of SES through the beliefs channel on these choices. We find that, while SES measures like income or education on their own directly predict the interest in investing in stocks, or buying homes, durables, or cars, there exist indirect effects of income and education through the belief channel that account for a significant fraction of the total effect of the SES variables on these decisions—for example, close to 25% in the case of home buying attitudes. We also specifically analyze stock market investment decisions and beliefs regarding stock returns in particular, and show that SES-induced beliefs account for a significant fraction, up to 47%, of the total effect of the SES variables, namely, income and education, on the decision to invest, and on the share of income invested in equities.

At a deeper psychological level, a number of mechanisms could potentially generate the procyclical wedge in macroeconomic expectations between high and low-SES individuals in our data. One possibility is that low-SES individuals underappreciate the informativeness of public signals about the macroeconomy relative to (pessimistic) prior beliefs formed based on their personal economic environment. The expectations evidence can also be explained with a variant of the local thinking framework of Gennaioli and Shleifer (2010) and Gennaioli, Shleifer, and Vishny (2012) in which a low-SES individual neglects good states of the world that she does not view as representative. Alternatively, the time-varying pessimism could also be generated by a confirmation bias as in Rabin and Schrag (1999) if low-SES individuals have a tendency to misinterpret good macroeconomic signals as bad signals. We offer tentative evidence based on a variable in the MSC that records the extent to which survey respondents have heard positive or negative business news. We find that news perception of high and low-SES individuals is similar on average, but low-SES individuals report less positive news heard in booms and less negative news heard in recessions. This symmetric pattern fits well with the misperceived signal informativeness theory, but is not predicted by the local thinking and confirmation bias theories. While we do not view these tests based on a rather crude measure of signal perception as conclusive, they are suggestive of a role for misperceived signal informativeness. It would be interesting for future research to investigate this channel with a more refined measure of signal perception, perhaps ideally with experiments in the field or laboratory.

In terms of economic implications, the results in this paper can help shed light on the empirical pattern documented by Vissing-Jorgensen (2003), Campbell (2006) and Calvet, Campbell, and Sodini (2007) that households with lower education, income or wealth are substantially less likely to participate in the stock market. The causes of non-participation are still unclear. Standard explanations involve participation costs (Vissing-Jorgensen (2002)), but they still appear to leave a substantial part of the non-participation unexplained (Andersen and Nielsen (2011)). Our findings indicate that beliefs could be part of the explanation for why some individuals do not participate: whatever the actual cost or perceived cost of participation, pessimistic expectations lead to lower perceived benefits from participation and hence to low rates of participation of low-SES individuals.

Stock market non-participation can imply welfare losses for households, as discussed in Calvet, Campbell, and Sodini (2007). Thus, pessimistic macroeconomic expectations can have welfare consequences for low-SES individuals. Moreover, non-participation of low-SES households could result in heterogeneity in wealth returns that is correlated with the level of wealth, which in turn plays a role in generating wealth inequality (Favilukis (2013), Gabaix, Lasry, Lions, and Moll (2016)). By limiting their investment opportunity set, the pessimistic low-SES households may perpetuate their disadvantaged financial position.

Pessimistic expectations about future business conditions or unemployment could further induce individuals from low-SES backgrounds to have low levels of investments along other dimensions also, such as pursuing higher education, better health, or starting a new business. While there is no direct evidence for this implication of our work, existing relevant findings seem to support it. For example, Kearney and Levine (2016) document that children from lower SES families are more likely to drop out of high school, relative to their better-off peers, and attribute this to more pessimistic subjective estimates of the likelihood of economic success among lower SES individuals. In this sense, our results also connect to the theory of Piketty (1995) in which individuals draw on the personal economic experience of their family dynasties to form beliefs about the returns to effort in the economy.

Our work on macroeconomic expectations builds on earlier work that is focused on stock return beliefs. Kezdi and Willis (2011) document links between income and education and stock market return beliefs using a sample of 55- to 64-year olds from the Health and Retirement Study. Their estimation is based on a single survey wave from 2002. Kuhnen and Miu (2017) complement their experimental work with evidence on SES-related stock return beliefs heterogeneity based on a single Qualtrics survey cross-section. Our finding in this paper that SES-related beliefs heterogeneity is subject to strong business cycle dynamics—with the beliefs wedge between high and low-SES individuals almost disappearing during recessions—highlights that it is important to study samples with a much longer time dimension. Moreover, we show that SES variables are related to macroeconomic expectations more generally, not just stock return expectations.

Our work is further related to an emerging literature showing that individuals' macroeconomic expectations are influenced by personal circumstances that are specific to an individual or a group of people. While our focus is on an individual's current economic situation, which is strongly influenced by a person's history of idiosyncratic shocks and initial conditions, earlier work has found links between the macroeconomic history that individuals of a given cohort have experienced, and their expectations and investment decisions. Individuals in cohorts that experienced bad macroeconomic conditions subsequently avoid risky financial choices, either as investors (Malmendier and Nagel (2011)) or as managers (Malmendier and Tate (2005), Malmendier, Tate, and Yan (2011)). Evidence in support of this belief channel is provided by Malmendier and Nagel (2016), who find that differences in inflation experiences across cohorts strongly predict differences in the expectations of these cohorts regarding future inflation levels. Experimental evidence in Kuhnen (2015) shows that individuals faced with sequences of negative payoffs form overly pessimistic beliefs about the quality of the available investments. Kuchler and Zafar (2016) show that individuals' expectations about national U.S. house prices depend on their personally experienced house price history in their local geographic area, and expectations about the national unemployment rate are influenced by personal experiences of unemployment.[1] A common thread in these studies is that expectations about a macroeconomic variable (e.g., house prices) are related to personal experiences of the realized cohort-specific or geographically local history of the *same* variable. In contrast, the effect that we study is one where a person's own economic situation is correlated with a broad range of *macroeconomic* expectations.

2 Data

Our data span the period 1978-2014, at a monthly frequency. Each month, approximately 400 individuals are recruited for the Michigan Survey of Consumers, and are asked to express their beliefs about future values of several macroeconomic variables. The survey is based on a nationally representative group of respondents, sampled using landline and cellular phone numbers (Curtin and Dechaux (2015)). In our analysis, we weight observations with the household sample weights provided by the MSC. These sample weights adjust, among other things, for differential non-response by demographic characteristics.[2]

[1] Amonlirdviman (2007) documents that people with low income or education are more pessimistic about their own personal situation, and presents a model where these individuals suffer from low self-control, and the optimal response to self-control problems is to become defensively pessimistic about one's future prospects.

[2] Curtin, Presser, and Singer (2002) investigate the role of survey non-response on expectations collected by the MSC, and find that demographic characteristics, including income and education, do not have sizeable effects on the probability of agreeing to be part of the survey. Moreover, the authors find no evidence that the likelihood of participating in the survey is a function of the respondents' macroeconomic optimism.

Table 1: Data Definitions

Variable	Description	Source	Values
PSTK	Percent Chance of Invest Increase 1 Year	% Chance of investment increase in 1 year: What do you think is the percent chance that a one thousand dollar investment in a diversified stock mutual fund will increase in value in the year ahead, so that it is worth more than one thousand dollars one year from now?	0 - 100%. Only available during 2002-2014.
BEXP	Economy Better/Worse Next Year	And how about a year from now, do you expect that in the country as a whole business conditions will be better, or worse than they are at present, or just about the same?	Better a year from now About the same Worse a year from now
BUS12	Economy Good/Bad Next 12 Months	Now turning to business conditions in the country as a whole–do you think that during the next 12 months we'll have good times financially, or bad times, or what?	Good times Good with qualifications Pro-con Bad with qualifications Bad times
BUS5	Economy Good/Bad Next 5 Years	Looking ahead, which would you say is more likely – that in the country as a whole we'll have continuous good times during the next 5 years or so, or that we will have periods of widespread unemployment or depression, or what?	Good times Good with qualifications Pro-con Bad with qualifications Bad times
UNEMP	Unemployment More/Less Next Year	How about people out of work during the coming 12 months –do you think that there will be more unemployment than now, about the same, or less?	More unemployment About the same Less unemployment
1-Yr Change in Personal Finances	Personal Finances Relative to A Year Ago	Would you say that you are better off or worse off financially than you were a year ago?	Better now Same Worse now

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... table 1 continued

Variable	Description	Source	Values
County unemployment	Bureau of Labor Statistics	County Unemployment, Monthly	
County personal income	Bureau of Economic Analysis	County Income/Capita, Annual	
Invest	Invest in equities	Do you have stock investments?	Yes No
Invest Share	Overall amount invested in equities, relative to current annual income	Defined as ln (Amt Invested/Income), if Invest=1	
HOM	Home Buying Attitude	Generally speaking, do you think now is a good time or a bad time to buy a house?	Good Pro-Con Bad
DUR	Durables Buying Attitude	Generally speaking, do you think now is a good or a bad time for people to buy major household items?	Good Pro-Con Bad
CAR	Car Buying Attitude	Speaking now of the automobile market –do you think the next 12 months or so will be a good time or a bad time to buy a vehicle, such as a car, pickup, van, or sport utility vehicle?	Good Pro-Con Bad

In total, there are 189,590 person-month observations in our sample. The macro belief variables we study are $PSTK$, $BUS12$, $BUS5$, $BEXP$ and $UNEMP$. Table 1 presents the survey questions used to measure the belief variables, and the respondents' possible answers. $PSTK$ is the respondent's subjective probability that the US stock market will have a positive return over the next 12 months. *BUS12,* $BUS5$ and $BEXP$ measure expectations about the evolution of the overall business environment over the following 12 months or 5 years, and *UNEMP* measures expectations about the evolution of the national unemployment rate over the following 12 months. We rescale the belief variables except $PSTK$ to vary between -1 to 1, and we set the sign such that higher values imply optimism. To calculate an aggregate measure of macroeconomic optimism, we standardize each of these individual beliefs, and average the standardized values. Because $PSTK$ is only available starting in June 2002, $OPTINDX$ is the average of four standardized beliefs ($BUS12$,

$BUS5$, $BEXP$ and $UNEMP$) prior to that time, and it is the average of five standardized beliefs ($BUS12$, $BUS5$, $BEXP$, $UNEMP$, and $PSTK$) after that month.

One could be concerned with the inclusion of PSTK in our OPTINDX measure because the PSTK-related question is worded in a way that may be difficult for an average respondent to understand. Relatedly, stock market beliefs may be inherently different from other macroeconomic beliefs because investing in equities could be an unfamiliar or irrelevant topic for some households. Moreover, a data-driven weighting of the 5 belief measures in OPTINDX may be preferable instead of simply equally weighting them. In unreported results we experiment with alternative specifications of OPTINDX. In one case we exclude PSTK from our index; in another, we use the first principal component weights to construct our OPTINDX. We find that these alternative constructions of the OPTINDX measure yield qualitatively similar results, both in terms of point estimates and significance in our main regressions.

We choose income and education as indicators of the socioeconomic status of households. We restrict our analysis to individuals 24- to 75-years old because income or college degree completion may not be meaningful SES measures for very old or very young adults. Next we create percentiles of real income (in 2014 dollars) within each year and age group (25-29, 30-34, .. 70-74), which we then divide by 100 and label *Income rank*. Therefore, a change of one percentile implies an income rank change of 0.01, and a change of 10 percentiles implies an income rank change of 0.1. We use this as one of the socioeconomic status variables because relative income compared to peers may matter more than dollar income, but we obtain broadly similar effects if we use dollar income rather than income rank. *College Degree* is a binary variable which takes value 1 if the respondent has at least a college degree.

To measure recent changes in an individual's personal economic situation, we use the variable *1-yr Change in Personal Situation*, provided in the Michigan survey for each respondent, which takes values -1, 0 or 1 if the individual reports being worse off, the same, or better-off than a year ago, in terms of their personal finances. For a more objective measure of changes in the individual's economic environment, we use data from the Bureau of Labor Statistics on the unemployment level and data on per-capita income from Bureau of Economic Analysis of the county where the

Table 2: Summary Statistics

Expectations data are collected monthly during 1978-2014, with the exception of PSTK (stock market expectations), which is available only during 2002-2014.

	N	Mean	Median	StdDev	Min	Max
OPTINDX	189590	0.008	0.044	0.733	-1.540	1.771
PSTK	56821	0.483	0.500	0.293	0.000	1.000
BUS12	173504	-0.014	0.000	0.964	-1.000	1.000
BUS5	178834	-0.084	-0.500	0.861	-1.000	1.000
BEXP	186249	0.075	0.000	0.694	-1.000	1.000
UNEMP	187984	-0.195	0.000	0.694	-1.000	1.000
Income Rank	189590	0.476	0.47	0.288	0.01	1.000
College Degree	189590	0.341	0.000	0.474	0.000	1.000
1-Yr Change in Personal Finances	189223	0.057	0.000	0.848	-1.000	1.000
County Unemployment Rate	68548	6.419	5.800	2.616	1.100	31.200
County Personal Income (Real $)	68563	43360	41142	12211	15119	139516
Invest	78825	0.622	1.000	0.485	0.000	1.000
Annual income (Real $)	189590	69926	57591	61256	1.6	1041090
Amt Inv(Real $)	43168	232604	80654	605282	985	14612452
Log(Amt Inv(Real $))	43168	11.207	11.298	1.591	6.893	16.497
Log(Inv share)	43168	-0.157	-0.077	1.402	-5.565	5.085
HOM	186318	0.384	1.000	0.913	-1.000	1.000
DUR	180019	0.466	1.000	0.858	-1.000	1.000
CAR	180065	0.307	1.000	0.936	-1.000	1.000

respondent resides.[3]

Table 2 presents summary statistics for the variables that capture the personal economic situation, beliefs, and household economic choices of the individuals in the sample. In our data, 34.1% of people have completed at least a college degree. The median real household income (in 2014 dollars) of the participants in the survey is $57,591, but there are clear outliers in the income distribution, as can be seen in Table 2. The average value for the overall amount a person has invested in equities as of the time of the survey is about 85% of the annual income of that individual.

Given the construction of the aggregate belief measure $OPTINDX$ as a mean of standardized variables, in our sample spanning 1978-2014 the average $OPTINDX$ is close to zero. The average estimates for $BUS12$ and $BUS5$, which are beliefs regarding whether there will be good or bad economic times over the next 12 months or 5 years, are -0.014 and -0.084, respectively. Given that the scale for these two variables spans -1 to 1, these averages indicate that expectations about future economic times have not been overly pessimistic or overly optimistic during the 37 years studied here. The same holds true for $BEXP$, the belief regarding general business conditions over the next year, whose average in the sample is 0.075. The belief regarding whether unemployment will be lower or higher over the next year, $UNEMP$, has the most negative sample average, -0.195, indicating that survey participants were the most pessimistic about this particular aspect of future economic conditions. During 2002-2014, the time frame for which this measure is available, the average estimate of $PSTK$, the probability that a U.S. stock market investment would increase in value in the next 12 months, is 48.3%, with a standard deviation of 29.3%.

We also use several variables that capture the individuals' decisions regarding stock market investments, namely whether they invest in equity ($Invest$), as well as the share of income invested in the stock market (*Invest Share*), and their attitudes at the time of the survey towards buying a home (HOM), buying durables (DUR) or cars (CAR). About 62% of individuals in our sample participate in the stock market, and on average responses regarding whether it is a good time to

[3]Because the county of residence is not publicly available in the Michigan survey, we had the county-level information merged in by the staff who oversee this survey, but the resulting dataset that we can use does not have the actual county identifiers. The county-level data could only be merged in for MSC observations during 2000-2014. The merging is done such that the county unemployment level is as of the month preceding the survey and the county per-capita income is as of the year preceding the survey. This is done to reflect the most current information available to the respondents.

purchase a home, durables or cars are positive. For example, the variable HOM, which can take values of -1, 0 or 1, indicating either negative, neutral or positive attitudes towards buying a home, has an average of 0.384, and thus is more tilted towards the positive end of the response scale.

3 Expectations Heterogeneity by Socioeconomic Status

3.1 Beliefs and SES

We start by examining differences in macroeconomic expectations by SES, measured along the dimensions of income and education. Figure 1 plots the monthly average values of our optimism index, OPTINDX, for individuals in the highest and lowest income quintiles (in their respective age groups) from 1978 to 2014. The figure shows that there is a remarkably persistent wedge in beliefs between high- and low-SES individuals: In almost every month during the sample period, individuals with higher income or higher education had more optimistic macroeconomic expectations. Moreover, the disagreement between households of different SES is pro-cyclical. During recessions, it shrinks to close to zero.

Among the different macroeconomic expectations variables, we are particularly interested in beliefs about future stock market returns, as we have the most direct measures of closely related economic decisions—stock market investments—for this type of belief. Figure 2 plots the monthly averages of PSTK, individuals' stated probability that the US stock market will have a positive return over the following 12 months, for high- and low-SES groups. As the figure shows, the time series of the PSTK beliefs wedge looks very similar to the wedge in OPTINDX that we examined earlier: High-SES individuals are more optimistic than low-SES individuals in virtually every month throughout the whole sample in which PSTK is available and the wedge is pro-cyclical.

Additional figures in Appendix A show that there exists an SES-induced wedge in beliefs for each component of the optimism index OPTINDX (in addition to $PSTK$), namely, $BUS5$, $BUS12$, $BEXP$ and $UNEMP$, and that recessions lead to a lower SES-related gap for each of these types of macroeconomic expectations.

Table 3 presents these results more formally in terms of a regression. Dependent variables

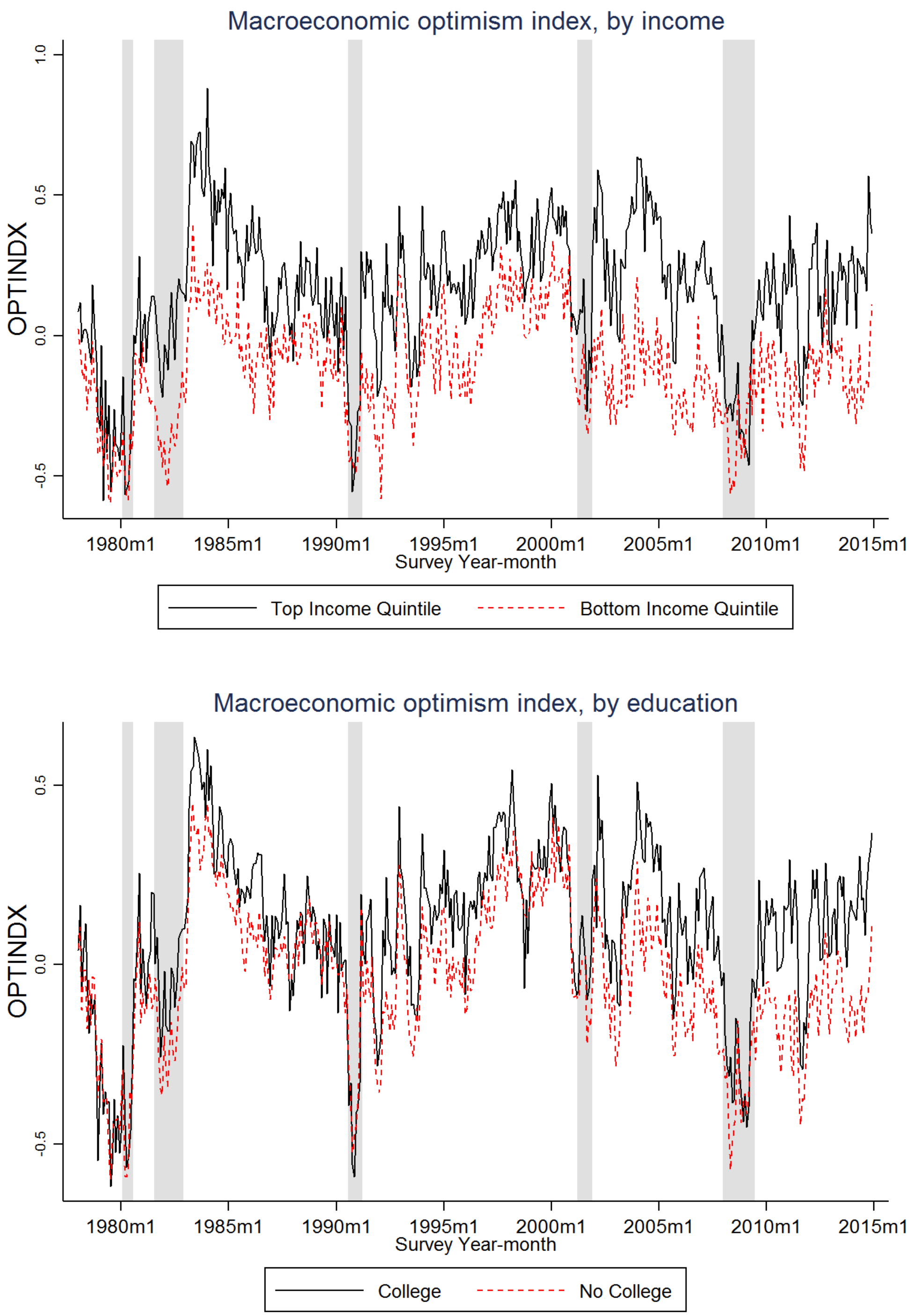

Figure 1: Macroeconomic optimism during 1978-2014 by SES level. Monthly data. Income quintiles are defined within year-age groups. Shaded areas represent NBER recession periods.

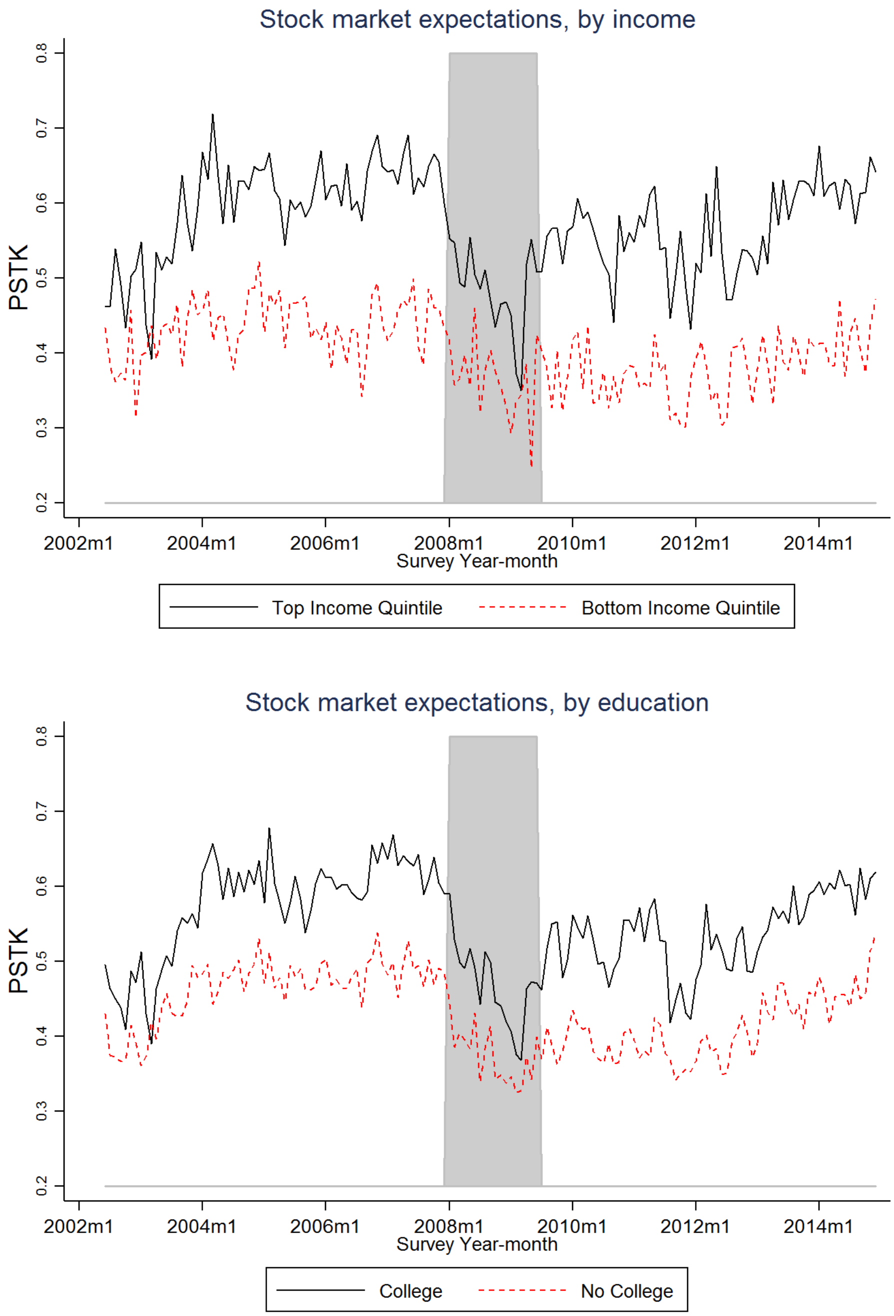

Figure 2: Stock market expectations during 2002-2014 by SES level. Expectations refer to individuals' stated probability that the US stock market will have a positive return over the following 12 months. Monthly data. Income quintiles are defined within year-age groups. Shaded areas represent NBER recession periods.

Table 3: Macroeconomic Expectations, Socioeconomic Status, and the Business Cycle

The table presents OLS regressions with macroeconomic expectations as the dependent variable (where higher values indicate optimism). OPTINDX : Overall macroeconomic optimism index; PSTK: Probability of stock market gain in next 1 year; BUS12: Financially good times in next 12 months; BUS5: Financially good times in next 5 years; BEXP: Overall business environment in next 1 year; UNEMP: Unemployment increase/decrease in next 1 year. Controls include dummies for year-month, age, gender, and marital status. Standard errors are clustered by individual and year-month, and $t-$statistics are shown in parentheses.

	OPTINDX	PSTK	BUS12	BUS5	BEXP	UNEMP
Income Rank	0.304	0.164	0.317	0.392	0.133	0.141
	(28.21)	(25.52)	(22.73)	(32.80)	(13.66)	(13.28)
College Degree	0.058	0.072	0.021	0.083	0.019	0.029
	(9.65)	(21.45)	(3.09)	(13.66)	(3.55)	(5.27)
Recession × Income Rank	-0.076	-0.053	-0.242	-0.067	0.094	-0.110
	(-2.52)	(-2.54)	(-7.08)	(-2.23)	(2.95)	(-3.49)
Recession × College Degree	-0.039	-0.016	-0.067	-0.025	0.012	-0.054
	(-3.00)	(-2.11)	(-4.27)	(-1.70)	(0.87)	(-4.54)
Observations	188614	56747	172646	177951	185310	187032
Adjusted R^2	0.115	0.114	0.136	0.082	0.052	0.071

in the models in the table are measures of macroeconomic expectations: the aggregate optimism measure $OPTINDX$ in the first column, and its separate components in the following five columns. Independent variables include the person's income rank as a percentile (defined with respect to the person's year-age group), an indicator for whether the person has a college degree or higher education, and interactions of an NBER recession indicator with the two SES measures.[4] All regressions in the paper also include fixed effects for the year-month of the survey, as well as indicators for the respondents' age, gender, and marital status. The standard errors are clustered by time, specifically by year-month, as well as by respondent.

In line with the patterns seen in the figures, Table 3 shows that people's SES characteristics are

[4]We examine other measures of SES related to the person's income. Specifically, we calculated their percentile income rank (always relative to people in the same age bin) in terms of the ratio of the respondent's income to their household size, or in terms of the ratio of the respondent's income to the median income in their county of residence, or in terms of the ratio of their household-size adjusted income to the median income in the county of residence. The effects of these alternative measures of SES on macroeconomic expectations are similar to the effects we obtain in our main specification in Table 3. We present these effects in Table A1 in the Appendix.

highly significant predictors of their beliefs regarding future macroeconomic conditions ($PSTK$, $BUS12$, $BUS5$, $BEXP$, $UNEMP$), as well as of their aggregate optimism index $OPTINDX$. For each of our five measures of beliefs, we find that having a higher income rank among people in the same age category and in the same year, and having a college degree are significant predictors of the level of optimism in the respondents' expectations. When the dependent variable captures expectations about future stock market returns ($PSTK$), we find that during non-recession months, for an increase from the bottom to the top most rank of respondents' income, the probability they estimate for the U.S. stock market to have a positive return over the next year increases by 16.4%. People with at least a college degree, on average believe that the probability of positive stock market return is 7.2% higher than people without a college education.

Similarly, we find that during non-recession months, those with higher SES have significantly more optimistic expectations for $BUS12$, $BUS5$, $BEXP$, $UNEMP$ and have higher values for the overall belief measure $OPTINDX$. For example, an increase of a person's income rank from bottom to top most rank leads to an average increase of 0.304 in OPTINDX. A change by one quintile (20 percentiles) in income rank leads to an increase of $0.304 \times 0.2 \approx 0.06$ in OPTINDX. Having a college degree has a similar effect, as it leads to an increase in OPTINDX of 0.058. All of these effects are statistically significant at $p < 0.05$ or better.

To allay concerns about overstating the significance and stability of these estimates, we re-run the models in Table 3 but only in the subsample of first-time participants in the MSC. The results are similar, as shown in Table A2 in the Appendix. We also re-run our main regressions from Table 3 by splitting the sample in halves, as well as in thirds, and find that the effects are not driven by a small subsample of years.

Judging the economic significance of the results in Table 3 is not quite straightforward as the survey-based beliefs measures we use as dependent variables have quite substantial measurement noise, including occasionally non-sensical outliers. One way to gauge the economic significance is to compare the cross-sectional variation related to the SES variables with typical business cycle time-variation in the macroeconomic belief variables. Based on Figure 1 we can see that OPTINDX averaged across high- and low-income groups moves, at the most extreme, by about one unit from peak-to-trough during the business cycle. In comparison, focusing on non-recession months (i.e., ignoring the interaction term for now) the regression results in Table 3 imply that moving from the bottom quintile of the income distribution to the top quintile changes OPTINDX by a quarter, i.e., by about a quarter of the peak-to-trough movement in OPTINDX. Having a college degree implies a change of about 6% of peak-to-trough OPTINDX. For PSTK, the typical peak-to-through movement in Figure 2 is about 0.30, and so a change from the bottom to top income quintile implies a change in PSTK of about half this amount. A change in the college education status implies a change in PSTK of about a quarter of the peak-to-trough movement. This comparison to business-cycle variation shows that the SES-related heterogeneity in expectations is substantial and economically significant.

The regression results in Table 3 further show that the size of the beliefs wedge between high- and low-SES individuals is state-dependent. Consistent with Figures 1 and 2, the coefficient estimates on the interaction terms of the NBER recession indicator and either SES measure show that the SES-related wedge in expectations is significantly smaller during recessions. In the case of education, the effect of a college degree on OPTINDX is two thirds smaller during recessions (instead of 0.058, it is 0.058-0.039, or 0.019). The effect of income percentile rank is a quarter smaller (instead of 0.304 it is 0.304-0.076, or 0.228) during recessions, although Figure 1 shows that the wedge even completely disappeared between the lowest and highest income quintiles for a few months during the last three recessions.

3.2 Heterogeneity in forecast bias

Our analysis so far has documented two broad empirical patterns: first, lower SES people hold more pessimistic macroeconomic beliefs, and second, during recessions the difference in macroeconomic beliefs between those with high and low SES diminishes considerably. To understand the reasons for this time-varying beliefs wedge, it would be useful to know whether high or low-SES individuals are closer to the "truth." Figuring this out is not quite a straightforward exercise, though.

First, it is not clear what the "truth"—i.e., the rational forecast—is. With parameter and model uncertainty, we, as econometricians, do not have knowledge of the true model of macroeconomic dynamics. We deal with this issue by taking the median from the Survey of Professional Forecasters (SPF) as our benchmark forecasts. These are arguably among the most sophisticated macroeconomic forecasts available.[5] The SPF does not have one-year stock market return forecasts, so we need a different benchmark for PSTK. We assume that stock returns are close to unpredictable, and so we use an estimate of the unconditional probability of a positive 12-month stock market returns as benchmark. We estimate it based on the fraction of positive 12-month returns (using overlapping monthly windows) of the CRSP value-weighted index since 1926.

Second, for some of the expectations variables in the Michigan Survey, there is no directly corresponding forecast in the SPF. We deal with this issue as follows:

- UNEMP can be matched with the unemployment forecast in the SPF. Since the Michigan Survey asks about the change in unemployment over the next 12 months, we compare it with the difference between the three-quarter ahead forecast, $t+3$ of the level of unemployment, and the end of prior quarter $t-1$ "nowcast."[6]

- For the three business conditions variables in the Michigan Survey, BEXP is the one that is closest to a change in real GDP so we match BEXP with RGDP forecasts in the SPF. BEXP is based on the question "And how about a year from now, do you expect that in the country as a whole business conditions will be better, or worse than they are at present, or just about the same?" (see Table 1). It seems reasonable to think of good business conditions as a high RGDP growth rate and bad business conditions as a low RGDP growth rate, similar to typical classifications into recessions and non-recession periods. Therefore, we calculate a change in the forecasted growth rate of RGDP. Since the SPF contains RGDP level forecasts, we calculate the average forecasted change in log GDP over the four quarters from the end of the current quarter t to quarter $t+4$ and we subtract the change from the end of the prior quarter, $t-1$ to t.

[5] Carroll (2003) compares the time series of mean inflation forecasts from the SPF and the Michigan Survey with subsequently realized inflation and finds that the SPF forecast has a much smaller mean-squared error than the Michigan forecast. Croushore (1998) cannot reject unbiasedness of the mean SPF forecast and Mankiw, Reis, and Wolfers (2003) cannot reject unbiasedness of the median forecast.

[6] Using the prior quarter rate from the SPF rather than from published unemployment series avoids the problem that current versions of the unemployment series have been revised ex-post and do not represent information that was available in real time.

- PSTK is matched to a benchmark computed from realized stock returns as explained above.

The third issue is that the UNEMP and BEXP variables in the Michigan Survey of Consumers are categorical and hence do not directly map into the continuous SPF unemployment and RGDP forecasts. To make them comparable, we discretize the SPF forecast based on the assumption that any forecasted change in the unemployment rate or the RGDP growth rate within one standard deviation (calculated over the full sample since 1978) above or below zero corresponds to the "Same" category for BEXP and UNEMP, while a change above or below corresponds to better or worse conditions for BEXP and more or less unemployment for UNEMP.

Finally, the SPF is conducted only quarterly, while the Michigan Survey is monthly. The SPF is carried out in the middle month each quarter. We match the first two Michigan Survey months each quarter with the SPF from the prior quarter and the Michigan Survey wave from the third month each quarter to the SPF from the same quarter. Thus, the Michigan Survey is lagged somewhat relative to the SPF. This seems reasonable, as professionals are presumably faster in noticing and reacting to very recent information.[7]

Based on these definitions, we now calculate each month a forecast bias by subtracting from PSTK, BEXP, and UNEMP the corresponding value of the professional forecast. We then average these forecast biases for each (within age group-year) income percentile over the whole sample period. The results are presented in Figure 3. The plots also include a local linear regression fitted based on those income percentile averages.

The top panel shows that forecasts of individuals in all income ranks are, on average, too pessimistic relative to historical stock market performance. But beliefs of high-income individuals are closest to the historical frequencies. The middle panel presents the average forecast bias for RGDP. In this case, high-income individuals have forecasts that are on average unbiased while low-income individuals are too pessimistic. The bottom panel shows that high-income individuals are close to getting the unemployment forecast right on average, while low-income individuals forecast an unemployment rate that is too high, i.e., they are again too pessimistic.

In summary, the forecast bias results are consistent with our hypothesis that low SES induces

[7]For evidence on this, see Carroll (2003).

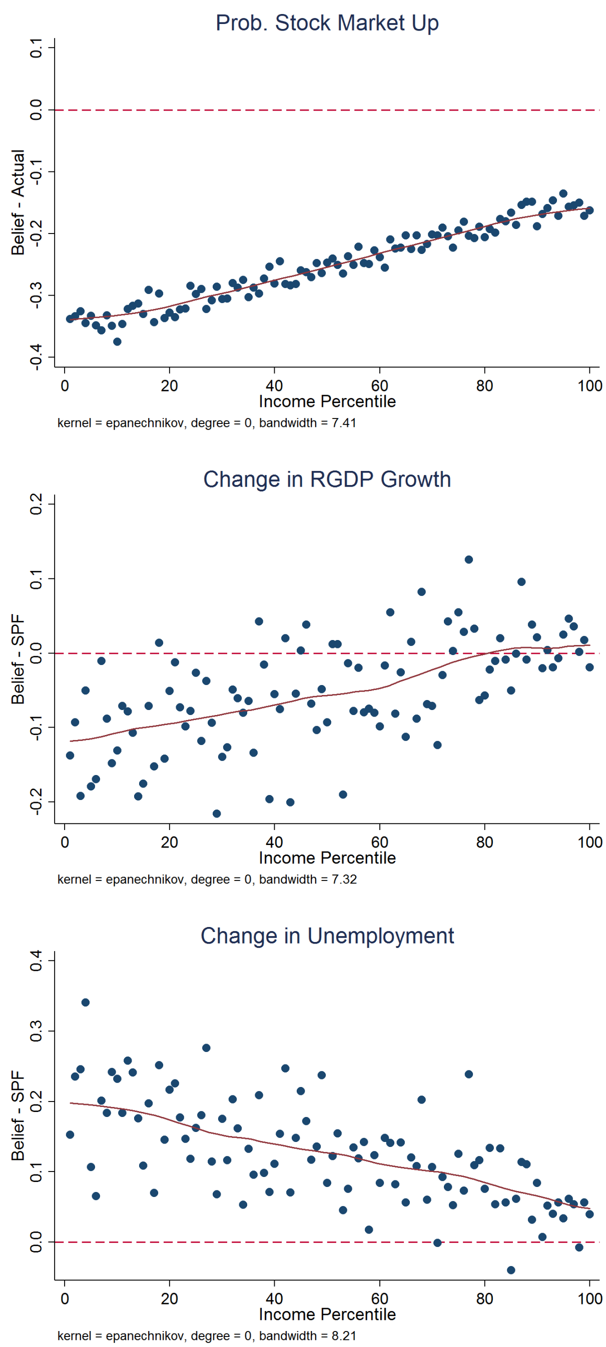

Figure 3: Average forecast bias by income percentile

Table 4: Macroeconomic Expectations and Socioeconomic Status among College-Educated Respondents

The table presents OLS regressions of macroeconomic expectations on SES within the subsample of college-educated respondents. Controls include dummies for year-month, age, gender, and marital status. Standard errors are clustered by individual and year-month, and $t-$statistics are shown in parentheses.

	OPTINDX	PSTK	BUS12	BUS5	BEXP	UNEMP
Income Rank	0.252	0.140	0.249	0.320	0.115	0.129
	(15.82)	(14.64)	(12.05)	(17.89)	(7.60)	(8.32)
Recession $\times$ Income Rank	-0.077	-0.009	-0.236	-0.054	0.084	-0.148
	(-1.93)	(-0.35)	(-4.50)	(-1.20)	(2.35)	(-3.44)
Observations	69448	25470	64272	66156	68405	69002
Adjusted R^2	0.114	0.088	0.155	0.074	0.061	0.098

pessimism. The fact that higher-income individuals' forecasts are closer to the "truth" is consistent with the notion that they are less prone to extrapolation from their own personal circumstances and experiences than low-income individuals.

3.3 Potentially confounding effects

Our hypothesis is that low SES causes pessimism. However, the correlation between SES and expectations in levels could potentially be explained by alternative theories as well. We now investigate whether such alternative factors could be driving the SES-expectations relationship.

One possibility is that the beliefs wedge between high- and low-SES individuals could be driven by differences in financial literacy. Lack of financial literacy could perhaps induce low-SES people to be more confused, in a pessimistic manner, about the macroeconomy. To address this concern, in the analysis in Table 4 we estimate similar models as in Table 3, but only for people with a college degree. We continue to find a significant and positive effect (0.252, $p < 0.01$) of $IncomeRank$ on people's aggregate expectations as measured by $OPTINDX$. This effect is similar in magnitude to that estimated in the specification in the first column in Table 3 (i.e., 0.304). In other words, even among those with high education, we find that individuals earning more money are more optimistic about future macroeconomic developments than their lower-income peers.

Table 5: Changes in Macroeconomic Expectations and Changes in Socioeconomic Status: Evidence from the Panel Sub-Sample

The table presents OLS regressions where the dependent variable is the within-individual change in a specific macroeconomic expectation and the independent variable of interest is the the within-individual change in income rank. Changes are calculated over six-month intervals between the two interview dates of the Michigan Survey panel sub-sample. The regression includes dummies for year-month. Standard errors are clustered by year-month, and $t-$statistics are shown in parentheses.

	OPTINDX	PSTK	BUS12	BUS5	BEXP	UNEMP
Income Rank change	0.0719	0.0589	0.0398	0.0622	0.0381	0.0711
	(3.36)	(3.07)	(1.21)	(2.16)	(1.58)	(2.83)
Observations	67287	20896	57398	60807	65325	66397
Adjusted R^2	0.063	0.021	0.056	0.018	0.028	0.033

More generally, there could be an underlying fixed personal characteristic—e.g., vulnerability to depression—that causes both general pessimism as well as poor economic choices that lead to low SES. Puri and Robinson (2007), for example, study the economic effects of dispositional optimism. This type of theory would imply an unobserved person fixed effect.

To address this issue, we use the panel sub-sample of the MSC. While most of the MSC sample consists of newly sampled respondents each month, a random sub-sample of them are re-interviewed once six months after the initial interview. We can use this panel structure to difference out unobserved fixed effects by looking at the relationship between changes in beliefs and changes in SES.

Specifically, we use this panel dimension to re-run a version of the baseline regressions in Table 3 with the dependent variable (expectations) and explanatory variable (income rank) differenced over the six-month window between the initial interview and the re-interview. As Table 5 shows, with the change in OPTINDX as the dependent variable, we still obtain a positive coefficient that is statistically significant. In terms of magnitude, it is about one-fourth of the coefficient in the levels regression in Table 3, indicating that the change in personal income rank over a short period of six months accounts for a substantial portion of the levels effect that we identified in Table 3. Thus, the fixed effects alternative mechanism is at best a partial explanation of the SES-expectations relationship. The regressions with the individual components of OPTINDX in the other columns on Table 5 all have positive coefficients on the income rank change and the difference from zero is statistically significant only for three out of the five variables.

The change in the size of the effect of SES on people's macroeconomic optimism as we move from the main sample of the Michigan Survey of Consumers (0.30, see Table 3,) to the within-individual analysis in the panel subsample (0.07, see Table 5) is not surprising. First, it is possible that the SES that shapes people's expectations and decisions only reflects components of income, wealth, and other SES determinants that are perceived as permanent. To the extent that transitory changes account for a substantial share of recent changes in income, differenced income rank captures changes in the permanent component, or long-run SES, only imperfectly. Whether people distinguish between transitory and permanent changes in this way is an interesting hypothesis that could be examined in a dataset where a person's SES can be tracked over many years. In the MSC we only observe SES at most two times (6-months apart) for one person, and this prevents us from measuring the relative effect of the recent versus long-run SES of an individual on their views about the macroeconomy. Second, and related, we would expect a substantial drop in the effect size from Table 3 to Table 5 due to measurement error. Transitory components of income could be one source of measurement error, but there is also likely a substantial survey response error. If measurement error in the level of SES has low serial correlation and true SES is persistent, the measurement error accounts for a much bigger fraction of the variation in the differences of measured SES than in the level of measured SES. As a consequence, attenuation bias in the differences regression is much bigger than in the levels regression. In Appendix C we calibrate a measurement error model to match recent evidence in Hyslop and Townsend (2018) from a comparison of survey responses and administrative panel data on individual earnings. These calculations suggest that measurement error can account for most and perhaps all of the drop in coefficient magnitude that we observe going from levels to differences in Tables 3 and 5. Taken together, these results suggest that there is not much room for fixed personal characteristics to drive the results in our baseline levels specification. Some caution is warranted, though, as the dynamic properties of survey measurement error are generally not well understood— the Hyslop and Townsend (2018) findings nothwithstanding—and so the precise magnitude of the measurement error distortion is difficult to pin down.

These differenced results also address a potential reverse causality story for our findings. Pessimistic beliefs could perhaps directly cause poor economic choices (e.g., portfolio and human capital investment decisions) that affect the SES measures that we use as explanatory variables in our baseline regressions. However, given the differenced panel regression results, this type of story seems a highly implausible explanation. To the extent that beliefs do affect choices, the effects of these choices on SES would presumably take much longer than six months to materialize in any significant way. Therefore, this story is an unlikely explanation for the contemporaneous correlation of belief changes and SES changes that we find in Table 5.

We can use the full sample of the MSC, without relying the panel structure, to provide further evidence that recent changes in economic circumstances affect individuals' expectations. Instead of direct measures of changes in income, we have to rely, however, on respondents' statements about past changes that they recall to have experienced. The survey variable we use for this purpose is the *1-yr Change in Personal Situation*, which can take the values -1, 0 or 1 to indicate whether people feel their finances have gotten worse, stayed the same, or improved in the past year.

The regressions reported in Table 6 in the second column add this variable to our baseline regression. Doing so raises the R^2 substantially and it lowers the coefficients on income rank by about a third. Thus, the change in economic situation captured by the added variable absorbs part of the SES level effect. While the interpretation is not as clean as in the differenced regression in Table 5, it would be difficult to explain this strong relationship between OPTINDX and recent changes in the survey respondents' personal financial situation under a personal fixed effects or reverse causality stories.

One potential concern regarding this interpretation is that the value of the *1-Yr Change in Personal Situation* variable may be an individual fixed characteristic, such that people who always say their situation has deteriorated recently are also people who always say the macroeconomy will fare poorly in the near future. However, as the analysis in Table 5 shows, macroeconomic expectations are not an individual fixed effect, since there is variation in this variable over time within person. Moreover, we find that there is substantial within-person variation in people's response regarding their *1-Yr Change in Personal Situation* and no persistence: the autocorrelation

Table 6: Macroeconomic Expectations and Socioeconomic Status, Controlling for Changes to Individuals' Personal Circumstances

The table presents OLS regressions with the macroeconomic optimism index OPTINDX as the dependent variable. Controls include dummies for year-month, age, gender, and marital status. Standard errors are clustered by individual and year-month, and $t-$statistics are shown in parentheses.

	OPTINDX	OPTINDX	OPTINDX 2000-2014	OPTINDX 2000-2014
Income Rank	0.304	0.214	0.347	0.221
	(28.21)	(21.15)	(20.56)	(12.57)
College Degree	0.058	0.050	0.112	0.098
	(9.65)	(8.67)	(12.27)	(11.09)
Recession × Income Rank	-0.076	-0.057	-0.224	-0.191
	(-2.52)	(-1.97)	(-5.51)	(-4.92)
Recession × College Degree	-0.039	-0.039	-0.070	-0.067
	(-3.00)	(-3.05)	(-3.57)	(-3.55)
1-yr Change in Personal Situation		0.159		0.184
		(48.02)		(31.15)
County Unemployment (%)				-0.004
				(-2.37)
County Personal Income(Real,$000)				0.002
				(4.58)
Observations	188614	188252	68450	68386
Adjusted R^2	0.115	0.145	0.101	0.145

of these perceived changes in overlapping one-year windows from the two interviews taken six months apart, is only 0.41—roughly what one would expect if there is zero autocorrelation for non-overlapping periods. Furthermore, as shown in Table A3 in the Appendix, within-person changes in individuals' perceptions about the change in their economic standing in the past year are significantly correlated with within-person changes in these individuals' macroeconomic optimism, whether we examine the overall optimism measure (OPTINDX), or the individual expectations measures that comprise this index.

Another concern is that individual-specific variation in mood could lead to spurious correlation between self-reported SES measures and reported macroeconomic beliefs in our baseline regressions. For example, someone who is depressed at the time of the interview might report a pessimistic expectation and, at the same time, provide the interviewer with an underestimate of her income. As a consequence, there could be a spurious positive correlation between income rank and macroeconomic expectation. Our results already indicate to some extent that this story is unlikely to be important since education, in addition to income rank, also plays an important role in shaping expectations. While underestimation of income rank by an individual in a depressed state may be plausible, underreporting of the own education level does not seem plausible. Nonetheless, a concern about spurious correlation of beliefs and income could remain.

To address this concern, we add local economic condition variables to the regression that are based on official economic statistics rather than on self-reports by survey respondents. Specifically, we use county-level data on the unemployment rate (monthly, from the Bureau of Labor Statistics) and the level of personal income (annually, in December 2014 dollars, from the Bureau of Economic Analysis) for the 2000-2014 period.[8] As Table 6 shows, these local economic condition variables help explain cross-sectional variation in macroeconomic beliefs. Both are statistically significant, and in terms of magnitudes a decrease of 0.5% in the local unemployment rate or an increase of $1,000 in local income have the same effect as a one percentile increase in the personal income rank of an individual. An alternative approach (untabulated) is to use the local economic conditions variables as instruments for income rank. Instrumented in this way, income rank still enters the regression significantly.

Finally, it is possible that survey respondents do not understand that they are asked to provide their beliefs about the macroeconomy, but instead, they think they need to provide their beliefs about their local economy. Several aspects of the data alleviate this concern. First, the questions used by the MSC clearly use words such as *changes in national unemployment*, with the goal of having respondents think about the macroeconomy when answering these questions. Second, the concern that people are simply reporting economic developments in their local area is unlikely to apply to the question regarding expectations about the return of the US stock market, since there is

[8]This merge of the MSC with county-level data cannot be done for times prior to year 2000 since the MSC does not include county identifiers before 2000.

no stock market at the local (e.g., county or state) level. Third, we found evidence inconsistent with the idea that respondents' answers are correlated with economic changes in the county where they reside. We specifically examined expectations about the unemployment rate. If respondents simply provide to the MSC their beliefs about unemployment rate changes in their local community, this would lead to the empirical patterns we observe in the paper if low-SES respondents live in areas with worse changes in unemployment during our sample period than the areas where the high-SES respondents live. We checked whether this condition holds. That is, we examined whether changes in unemployment year-to-year, objectively measured, are worse in counties where the low SES respondents reside, relative to counties where high SES respondents live. Figure A5 in the Appendix shows that this is not the case. If anything, during our sample period, 12-month unemployment rate changes were worse in counties where high SES respondents live. With SES defined by the level of education, we find no significant difference between the changes in 12-month unemployment in counties where respondents with a college education reside, relative to those where people without a college education live. Hence it is unlikely that our main results are simply an indication that respondents just describe what objectively is happening in their local community.

Overall, the results in this section are supportive of a robust and causal effect of SES on beliefs. Unobserved personal fixed effects, reverse causality, and spurious correlation through correlated measurement error can at most play a partial role, but they cannot be the main reasons for the strong empirical relationship between SES and macroeconomic expectations.

4 Importance of SES-driven expectations for household choices

The results so far indicate that a person's socioeconomic situation shapes their beliefs about future macro-level economic conditions, such that higher SES individuals hold more optimistic beliefs about future stock returns, unemployment and business conditions. In the next step of the analysis, our goal is to quantify the impact that SES has, through its influence on beliefs, on households' economic choices.

It is natural to expect that aspects of a person's SES will have a direct effect on that person's economic choices. For example, higher income individuals or those who are better educated are likely to be in a better position to invest in stocks relative to lower income individuals, perhaps because of access to retirement accounts at work, lower participation costs relative to wealth, or simply because they have money left to save after paying their bills each months. Similarly, higher SES individuals are less likely to face financial constraints and thus are more likely to consider purchasing homes, cars or durable goods.

Therefore, the total effect of SES on household choices comes from two sources: (1) the direct effect of SES on these choices—for example, because higher income leads to easier access to retirement accounts, and (2) the indirect effect of SES on these choices through the belief channel—for example, because higher SES individuals hold more optimistic beliefs about the distribution of stock returns, or other macroeconomic developments.

We can measure the relative importance of the direct and indirect effects of SES on people's economic choices using the analysis in Table 7. The dependent variables in columns two to six capture the respondent's investments in stocks ($Invest$ and $InvestShare$) and their assessment that it is a good time to purchase homes, durables or cars (HOM, DUR, CAR). The explanatory variables include our two SES dimensions (income rank and education), as well as the person's aggregate belief about future macroeconomic conditions ($OPTINDX$). If beliefs were measured without error, we could use OLS estimates of the coefficients on $OPTINDX$ in these regressions combined with the results from the regression of $OPTINDX$ on the SES variables in the first column to calculate how much of the effect of SES on choices is direct (SES $\Rightarrow$ Choice) and how much of it is indirect (SES $\Rightarrow$ Macroeconomic expectations $\Rightarrow$ Choice).

There is, however, substantial measurement error in $OPTINDX$. People's willingness and ability to carefully and precisely state their expectations in a survey is arguably limited and their responses could be influenced by random mood fluctuations that are not substantial and persistent enough to have consequences for economic choices. This measurement problem is likely much more severe for a relatively elusive concept like expectations of "general business conditions" than for a relatively clearly defined concept like family income or education level. In this sense, including a substantially mis-measured $OPTINDX$ along with more precisely measured SES variables in the

Table 7: Macroeconomic Expectations, SES, and Household Choices

The table presents IV regressions with the measures of investment choices and attitudes to consumption decisions as dependent variable in the panel sub-sample. OPTINDX is instrumented with lagged OPTINDX. Invest: Indicator for investment in equities; Invest Share: Log(Amt Invested/Income); HOM: Home buying Attitude; DUR: Durables Buying Attitude; CAR: Car Buying Attitude. Controls include dummies for year-month, age, gender, and marital status. Standard errors are clustered by year-month, and $t-$statistics are shown in parentheses.

	OPTINDX	Invest	Invest Share	HOM	DUR	CAR
Income Rank	0.324	0.714	0.296	0.311	0.156	0.263
	(24.93)	(64.48)	(5.37)	(19.03)	(10.15)	(16.07)
College Degree	0.055	0.100	0.280	0.065	-0.010	0.044
	(7.70)	(18.33)	(13.08)	(8.53)	(-1.32)	(5.28)
OPTINDX		0.057	0.204	0.308	0.312	0.363
		(9.02)	(7.59)	(27.54)	(28.70)	(31.92)
Observations	69549	32143	18226	68492	66511	66540
Adjusted R^2	0.112	0.287	0.228	0.181	0.095	0.084

regression could lead to a severe underestimation of the role of $OPTINDX$. Alternatively, rather than attenuation of the $OPTINDX$ coefficient, this type of measurement error could also induce spurious correlation between the choice measures and $OPTINDX$ if the mood fluctuations of the survey respondents affect the responses to the choice questions as well.

To address these issues, we return to the panel sub-sample of the MSC and we use each respondent's lagged $OPTINDX$ from the prior interview six months earlier as a instrumental variable (IV) for current $OPTINDX$. If measurement error and high-frequency mood fluctuations (e.g., due to a bad night's sleep) have sufficiently low persistence that they are not predictable with $OPTINDX$ measured six months earlier, then this IV approach removes the inconsistency caused by these distortions. The first stage results from our IV estimation are reported in the Appendix in Table A4.

The direct effects of the two SES measures on household choices are given by the estimated regression coefficients in the models in Table 7 for each of the two measures. As expected, we find that higher SES people are more likely to participate in the stock market, invest more money relative to their income in equities, and are more likely to believe that it is a good time to purchase homes, cars or durable goods. For example, the regression in the second column in Table 7 shows that an income rank increase from the bottom to the top most rank corresponds to 71% ($p < 0.01$) increase in the probability that the person invests in stocks. This is a large effect, considering that in our data, as shown in the summary statistics in Table 2, 62% of respondents invest in the stock market. Individuals with a college or higher education have a 10% ($p < 0.01$) higher probability of investing in stocks, compared to those less educated. Similarly, the results in the third column in Table 7 show that people with higher incomes and a college or higher education, conditional on investing in equities, have a higher amount of money, expressed as a fraction of their annual income, invested in stocks.

The regression models in the last three columns in Table 7 show that, in general, both dimensions of SES are significant and positive predictors of people's assessment that it is a good time to purchase a home, or a car or durable goods. For example, having a college or higher education translates into an improvement of 0.065 ($p < 0.01$) in the person's attitude towards buying a home, which is sizeable, given that the mean of this variable is 0.384 in our sample. The effect of increasing one's income rank by one quintile on the attitude towards buying a home is similar in magnitude ($0.311 \times 0.2 = 0.06$, $p < 0.01$) to that of having a college education. When the dependent variable captures the attitude towards buying durables, or cars, the estimated direct effects of the bottom to top income rank change are 0.156 and 0.263 respectively (both effects at $p < 0.01$). The only exception is that college educated people are not significantly different than those without a college degree to indicate that it is a good time to purchase durables. For car buying attitude, the direct effect of college education is an increase of 0.044 ($p < 0.01$) in attitude.[9]

Since in the regression models in Table 7 we control for the person's beliefs about future macroeconomic conditions, as measured by their overall optimism, $OPTINDX$, the above effects of SES on the person's decisions regarding investments and purchases represent the direct effects of SES on these decisions, holding fixed any indirect effects of SES through the belief channel.

[9]In Table A5 in the Appendix, we examine whether within-person changes in the six months between the two interviews of repeat participants predict within-person changes in attitudes regarding investment and consumption decisions, and find that to be the case, further supporting the idea that beliefs expressed in the survey are drivers of economic behavior.

To measure the indirect effects of SES, and the relative importance of the direct versus the indirect effects, we follow standard methodology used in mediation analysis. The results are presented in Table 8, and show that SES changes household choices through both the direct channel and the indirect, belief-related, channel.

For example, looking at the decision to invest or not in stocks (first row in Table 8), the direct effect of an increase of 10 percentile in a person's income rank is an increase of 0.0714 in the probability of investing, as shown earlier in the regression analysis in Table 7. The indirect effect of the same increase in the income rank, through the belief channel, is equal to the product of two quantities: the coefficient estimate on *Income Rank* in the regression model predicting the belief $OPTINDX$ in the first column of Table 7, and the coefficient estimate on $OPTINDX$ in the regression model from Table 7 that predicts the *Invest* variable. Thus, the indirect effect is $0.0324 \times 0.057 = 0.00184$. The total effect of an increase of 10 percentile in a person's income rank on the probability of investing in stocks is the sum of the direct (0.0714) and indirect (0.0018) effects, namely 0.0733. The importance of the indirect, belief-related channel, is given by the ratio of the indirect to total effect, which is equal to 2.52%. In other words, a person's income rank is a positive predictor of the decision to invest in stocks, and about 2.52% of the positive effect of income on the probability to invest is attributable to the beliefs that the person holds about future macroeconomic conditions. The rest of the effect is attributable to other income-related factors that are not about differences in beliefs.

The importance of the indirect beliefs channel is higher for other SES measures and household decisions. For example, analyzing the decision to invest in stocks, the indirect channel accounts for 3.06% of the positive effect of a college education. When analyzing the share of income invested in stocks, the indirect, belief-related channel, accounts for 18.26% of the positive effect of higher income rank, and 3.87% of the positive effect of a college education. When analyzing people's home buying attitude, the indirect, belief-related channel, accounts for 24.28% of the positive effect of higher income rank, and 20.75% of the positive effect of a college education. The indirect, belief-related channel accounts for 39.29% of the positive effect of higher income rank on attitudes towards durables purchases, and for 30.82% of the positive effects of either higher income rank,

Table 8: SES effects on Choices and Attitudes, Direct and Indirect through Macroeconomic Expectations

Model	Direct	Indirect	Total	Indirect/Total (%)
Invest: Income	0.714	0.018	0.733	2.52 %
Invest: Education	0.100	0.003	0.103	3.06 %
Invest Share: Income	0.296	0.066	0.362	18.26 %
Invest Share: Education	0.280	0.011	0.291	3.87 %
Home: Income	0.311	0.100	0.411	24.28 %
Home: Education	0.065	0.017	0.082	20.75 %
Durables: Income	0.156	0.101	0.257	39.29 %
Durables: Education	0	0.017	0.017	100 %
Car: Income	0.263	0.117	0.381	30.82 %
Car: Education	0.044	0.020	0.064	31.07 %

or higher education, on attitudes towards car purchases. Thus, the effects of SES on household choices and attitudes are in part driven by the differences in macroeconomic expectations of people with different SES.[10]

We interpret the respondents' answers regarding household decisions—such as choices concerning investing in the stock market, or attitudes towards buying homes, cars and durable goods—as good proxies for these individuals' actual economic behavior. That being said, we do not have administrative data to verify these survey answers. However, there are two reasons to believe that people's survey responses are truthful.

First, as shown earlier in our analysis, there is a clear relationship between respondents' expectations and their own household decisions as reported during the survey, which implies that the data on decisions can not be simply noise. This correlation between expectations and behavior is also found at the aggregate level, as shown for example in Carroll, Fuhrer, and Wilcox (1994), who document that the degree of optimism in MSC expectations is a strong positive predictor of the change over the following year in the aggregate level of personal consumption, including purchases of cars, other goods, and services.

Second, the survey measures of household behavior are strong predictors of aggregate macroe-

[10] An additional way to quantify the role of the SES-induced beliefs on household economic choices is to examine the contribution of these beliefs to the standard deviation of households' choices. In untabulated analyses, we find that this alternate approach leads to similar results as documented here.

conomic outcomes. For example, Cai, Deggendorf, and Wilcox (2015) find that the MSC aggregate response regarding whether it is a good time to buy a home is a strong and positive predictor of the volume of transactions in the housing market measured over the following year. In additional analyses of our own we find that the MSC respondents' monthly aggregate attitude DUR regarding purchasing durables is highly correlated (ρ=0.5, $p < 0.01$) with the aggregate contemporaneous monthly demand for durable goods, obtained from the FRED database of the Federal Reserve Bank of St. Louis. Similarly, we find that there is a high correlation (ρ=0.6, $p < 0.01$) between the MSC aggregate monthly attitude CAR towards buying cars, and the contemporaneous total car sales reported in the FRED database.[11]

Therefore, while we can not verify for each respondent whether their household decisions are truthfully reported, at least we observe that in the aggregate, the reports of individuals in the MSC correspond to actual macroeconomic outcomes.

So far in the analysis we have related several decisions of individuals to their aggregate belief about future economic conditions, $OPTINDX$. We will now turn towards analyzing a specific aspect of these beliefs, namely, the subjective probability that the U.S. stock market return will be positive over the next year ($PSTK$), to understand how it relates to the respondents' decision regarding making investments in stocks.

While SES-related variables such as income and participation costs impact whether a household invests in the stock market (e.g., Vissing-Jorgensen (2002)), our results so far suggest that SES-driven variation in beliefs about stock returns may also explain the variation across SES levels in terms of the decision to invest, and the fraction of income invested in stocks. We thus investigate the relative importance of the SES-related stock market belief channel, relative to that of other SES-related factors, on stock investment decisions.

The results in Table 9 indicate that SES measures, as well as $PSTK$, are positive predictors of a person's decision to invest in equities, and conditional on investing, of the share of income invested in stocks. The relative importance of the direct effect of SES measures, and their indirect

[11] The durable goods demand data and the total car sales data are available on the website of the Federal Reserve Bank of St. Louis at https://fred.stlouisfed.org/series/DGORDER, and https://fred.stlouisfed.org/series/TOTALSA, respectively. For our analysis we detrend these monthly time series to account for population growth.

Table 9: Stock Market Expectations, SES, and Investment Choices

The table presents IV regressions with the measures of investment choices as dependent variable in panel sub-sample. PSTK is instrumented with lagged PSTK. Invest: Indicator for investment in equities; Invest Share: Log(Amt Invested/Income). Controls include dummies for year-month, age, gender, and marital status. Standard errors are clustered by year-month, and $t-$statistics are shown in parentheses.

	PSTK	Invest	Invest Share
Income Rank	0.160	0.625	0.229
	(17.49)	(43.10)	(3.48)
College Degree	0.073	0.064	0.235
	(16.26)	(9.89)	(8.83)
PSTK		0.424	1.251
		(14.95)	(11.00)
Observations	21559	21400	13500
Adjusted R^2	0.122	0.251	0.219

effect through expectations, is illustrated in the results in Table 10. In columns (2)-(3) in Table 9, $PSTK$ is instrumented with 6-month prior $PSTK$. The first stage of these regressions are reported in the Appendix in Table A6.

As expected, the results in Table 9 show that, controlling for the belief about stock market returns, our SES measures are positive and significant predictors of both the invest decision, as well as of the share of income invested in stocks. In other words, income rank, and education directly influence a household's stock market investment decisions. However, as shown in our analysis in Table 3 and in the first column in Table 9, these SES measures also impact $PSTK$, the belief about whether the stock market return will be positive over the next year, which by itself, as seen in Table 9, influences the households' decision whether, and how much, to invest in stocks.[12]

The coefficient estimates in Table 9 allow us to estimate the direct and indirect (via the belief channel) effects of each of the SES measures on stock market investment decisions. Specifically,

[12] A possible concern is that there is a mechanical correlation between the expectations expressed by survey respondents and their declared choices, stemming from people's desire to look "consistent" in their survey answers. Specifically, an individual who declared that he does not invest in the stock market may later express pessimistic expectations about future stock market returns, to justify to himself and the experimenter why he holds no equities. Fortunately, the survey design used by the MSC staff alleviates this concern, because people are first asked to estimate the probability that the stock market will have a positive return, and only later are asked to calculate how much money, if any, they invest in stocks.

Table 10: SES effects on Investment Choices, Direct and Indirect through Stock Return Expectations

Model	Direct	Indirect	Total	Indirect/Total (%)
Invest: Income	0.625	0.068	0.693	9.76 %
Invest: Education	0.064	0.031	0.095	32.38 %
Invest Share: Income	0.229	0.200	0.429	46.58 %
Invest Share: Education	0.235	0.091	0.326	27.87 %

increasing a person's income rank by 10 percentiles increases the probability of stock market participation by 0.0625, and the share of income invested by 0.0229. The indirect effects of the same change in income rank on these two outcomes, through the belief channel, are obtained by multiplying the coefficient estimates on $PSTK$ in the first column in Table 9 and those in the second, and third column, respectively. Namely, the indirect effects of increasing the income rank by 10 percentiles on the probability of participation and on the share of income invested in stocks are increases of about 0.016 $\times$ 0.424=0.0068 and 0.016 $\times$ 1.251=0.02, respectively. The indirect effect of higher income, though inducing more optimistic beliefs about the stock market, represents 9.76% of the total effect of income on the participation decision (= 0.0625+0.0068), and 46.58% of its total effect on the share of income invested in stocks (=0.0229+0.02).

When examining the effects of education on the decision to invest in stocks and on the share of income invested, we also find sizeable indirect effects of this SES measure on the two decisions. Specifically, following the same procedure described earlier for quantifying the direct and indirect effects of income rank on stock investment decisions, we find that having a college degree increases the probability of investing in stocks by 9.5%, and 32.38% of this total effect of education on participation is coming from the indirect, belief-related channel. Also, having a college or better education increases the share of income invested in stocks by 32.6% and the fraction of this total effect that is driven by the belief channel is 27.87%. These results are summarized in Table 10.

Thus, we find that people who have higher incomes and are more educated are more likely to invest in stocks, and are willing to invest more of their income in these assets, and this is in part because they hold more optimistic beliefs about the stock market return distribution. Importantly, these effects are not limited to people from a specific region of the SES distribution, such as, for example, people with high education. In Table A7 in the Appendix we estimate a similar model as in Table 9 but separately for people with and without a college degree. The results show that respondents' expectations about future stock market returns, captured by the variable $PSTK$, have similar effects on people's decisions about investing in equities, across both high and low education participants.

5 Behavioral interpretation

We now discuss possible behavioral interpretations of the SES-related heterogeneity in macroeconomic expectations. This is not meant to be an exhaustive account of all possible behavioral explanations. There may be others than the ones that we discuss below that are observationally equivalent in terms of their implications for macroeconomic expectations. We focus on a small number of potential explanations that seem particularly plausible in this setting. We then offer some additional empirical evidence on heterogeneity in the perception of economic news that sheds some light on the relative merits of these explanations. While we do not believe that these tests can conclusively discriminate between these different behavioral interpretations, they are, at a minimum, suggestive about promising avenues for further research.

5.1 Theories of low-SES pessimism

Our main finding so far—low SES individuals are pessimistic on average in their macroeconomic expectations and the expectations wedge between high and low SES individuals is substantially bigger in booms than in recessions—is perhaps most naturally explained by a tendency of low SES people to put too much weight on their personal economic situation and too little weight on objective signals about the state of the macroeconomy. To express this hypothesis more precisely, consider a setting in which the true latent state of the economy is given by an IID random variable w_t, with $\omega_t \sim \mathcal{N}(0, \sigma_\omega^2)$, which is unobservable at t, but known one period later. Individuals are endowed with a prior belief about w_t with prior mean μ_0 that is influenced by their personal economic situation. Before seeing any macroeconomic data—in the present or historical data from the past—

μ_0 would represent their expectation of ω_t. However, we assume that relative to objective historical information about past realizations of ω_t, this personal-environment prior is uninformative. Thus, a rational individual with access to a long data set of historical data would come into period t with a data-based prior, $p(\omega_t)$, that reflects the population distribution $\omega_t \sim \mathcal{N}(0, \sigma_\omega^2)$. After receiving a noisy macroeconomic signal at time t,

$$s_t = \omega_t + e_t, \qquad \text{where} \quad e_t \sim \mathcal{N}(0, \sigma^2), \tag{1}$$

application of Bayes' rule yields a posterior distribution with mean

$$E[\omega_t | s_t] = \gamma s_t, \qquad \text{where} \quad \gamma = \frac{\sigma_\omega^2}{\sigma_\omega^2 + \sigma^2}, \tag{2}$$

which is the result of putting weight γ on the signal, weight $1-\gamma$ on the objective prior mean (which is zero), and zero weight on μ_0. We use $E[.]$ to denote expectations under the posterior beliefs of this rational individual. Under the posterior beliefs, we can decompose ω_t into an expected and unexpected component

$$\omega_t = \gamma s_t + u_t, \qquad \text{where} \quad E[u_t | s_t] = 0. \tag{3}$$

Now consider a low SES individual who underestimates the informativeness of objective signals and historical data compared with the prior based on the personal economic situation, perhaps because of a lack of trust in the informativeness of expert opinions, economic news, and other sources of macroeconomic information.[13] In terms of the model above, we can think of low-SES individuals putting some weight β, $0 < \beta \leq 1$, on the personal-environment prior μ_0. Given that the personal economic environment is less favorable for low-SES individuals, and the fact that conditioning on current low-SES also tends to select individuals that are more likely to have experienced recent bad shocks to their economic situation, we have $\mu_0 < 0$ for low SES individuals.

[13]Recent experimental evidence on house price expectations in Fuster, Perez-Truglia, and Zafar (2018) points towards such misperception of informativeness. They find that when low-SES individuals are offered a chance to acquire an informative signal about future house prices, low-SES individuals are less likely than high-SES individuals to pick the most informative signal.

Then,

$$\tilde{E}[\omega_t|s_t] = (1-\beta)\gamma s_t + \beta\mu_0, \tag{4}$$

where $\tilde{E}[.]$ denotes expectations under these biased beliefs. Taking the difference with (2), we obtain the bias

$$\tilde{E}[\omega_t|s_t] - E[\omega_t|s_t] = \beta(\mu_0 - \gamma s_t), \tag{5}$$

which is strongly negative following a good signal ($s_t > 0$) and small or even positive after a bad signal ($s_t < 0$). Thus, there is a pessimism bias on average, and the bias shrinks following bad signals, consistent with our empirical findings.

But there are alternative plausible behavioral biases that could give rise to similar expectations. For example, in the local thinking framework of Gennaioli and Shleifer (2010) and Gennaioli, Shleifer, and Vishny (2012), the decision maker neglects states that she does not view as representative. Within our continuous-state model, we can introduce local thinking through a truncated normal prior, where a normal distribution with mean zero and variance σ_ω^2 is truncated to $\omega_t \leq a_0$. Good states $\omega_t > a_0$ are neglected in the sense that they are assigned probability zero in the prior and therefore also in the posterior. Following (3), this implies that only states with

$$u_t \leq a_0 - \gamma s_t, \tag{6}$$

are considered possible. Applying Bayes' rule with this truncated prior, and using the properties of the truncated normal distribution, we obtain the posterior mean

$$\tilde{E}[\omega_t|s_t] = E[\omega_t|s_t, \omega_t < a_0] = \gamma s_t - \sigma\frac{\phi((a_0 - \gamma s_t)/\psi)}{\Phi((a_0 - \gamma s_t)/\psi)}, \tag{7}$$

where $\phi(.)$ and $\Phi(.)$ are the standard-normal PDF and CDF, respectively, and ψ is the posterior variance of u_t without truncation. Taking the difference with (2), we obtain the bias

$$\tilde{E}[\omega_t|s_t] - E[\omega_t|s_t] = -\sigma\frac{\phi((a_0 - \gamma s_t)/\psi)}{\Phi((a_0 - \gamma s_t)/\psi)}, \tag{8}$$

which is always negative and more so for high s_t. For large s_t (good signal), the bias is approximately $-\gamma s_t$, completely canceling the signal in (7), and for strongly negative s_t (bad signal), the bias is approximately zero. Thus, in terms of the behavior of subjective beliefs, the local thinking framework can deliver predictions that are similar to those from the misperceived signal informativeness hypothesis.

Similar expectations could also result from a misinterpretation of the signal in the form of a confirmation bias as in Rabin and Schrag (1999). Consider an individual that forms beliefs as in the rational case above, with the only exception being that good signals are sometimes misperceived by low SES individuals as bad signals—and more likely so the better the signal. More precisely, suppose that the probability that the signal is misperceived is equal to $1 - P(\omega_t < a_0 | s_t)$ (which implies that the probability of misperception goes to one as $s_t \to \infty$ and to zero as $s_t \to -\infty$), then,

$$\tilde{E}[\omega_t | s_t] = P(\omega_t < a_0 | s_t) E[\omega_t | s_t, \omega_t < a] + [1 - P(\omega_t < a_0 | s_t)] \, E[\omega_t | s_t, \text{misperception}] \qquad (9)$$

If we further assume that

$$E[\omega_t | s_t, \text{misperception}] = E[\omega_t | s_t, \omega_t < a_0], \qquad (10)$$

which means that if a signal is misperceived, it is, on average, perceived as a signal associated with a relatively bad state of the world $\omega_t < a_0$, then we obtain exactly the same subjective expectations as in the local thinking case (8).

We also note that a model based on ambiguity aversion could potentially produce observationally equivalent predictions for individuals' economic *choices*. Ambiguity aversion induces an individual to make choices as if she were pessimistic (Hansen and Sargent (2001)) and ambiguity about signal precision can induce an asymmetric reaction to news (Epstein and Schneider (2008)). To the extent that low-SES individuals are more ambiguity averse—perhaps, along the lines of Heath and Tversky (1991), because they feel less competent than high-SES individuals in judging the macroeconomic outlook—this could explain why low-SES individuals make *choices* as if they were pessimistic.

However, unlike the biased-beliefs models above, the ambiguity aversion model does not make clear predictions for the *beliefs* that individuals report in a survey. That an individual makes choices as if she were pessimistic does not imply that the individual would report pessimistic beliefs when asked about her expectations in a survey. Bhandari, Borovička, and Ho (2016), for example, assume so, but this is an additional assumption that does not follow from ambiguity aversion theory.

In terms of the predictions for subjective expectations of low-SES individuals in booms and recessions, the three behavioral theories—misperception of informativeness, local thinking, and conformation bias—can all deliver similar predictions matching our basic results. The theories would differ more in terms of their predictions for how individuals repeatedly update their beliefs after observing a sequence of signals. Unfortunately, our data only has a very short panel dimension that allows us to observe at most one change in expectations at the individual level which makes a multi-period study of individual updating behavior impossible. However, there is some information on economic news perception in the MSC that can help to at least tentatively shed some light on the relative merits of these three theories.

5.2 News perception

The MSC contains a variable that elicits the volume and tone of business news that survey respondents report to have heard recently. We can think of this variable as at least roughly capturing the news associated with the public signal s_t. Specifically, the variable *Business News Heard* takes the value of $-2, -1, 0, 1$, or 2, depending on how many business news the respondent reported having heard recently (0, 1, or 2), and whether they were positive or negative in nature (as coded by the MSC interviewer). A value of 2 means the respondent reported having heard 2 pieces of positive business news, while a value of -2 means the respondent reported having heard 2 pieces of negative business news. A value of 1 indicates the responded only reported having heard one piece of business news, and that it was positive. If the one piece of news heard was negative, the value of Business News Heard would be -1. Finally, this variable has the value 0 if either the responded did not recall hearing any business news lately, or whether one piece of news recalled was positive, and another was negative.

Table 11: Socioeconomic Status and Cyclicality of Business News Heard

The table presents OLS regressions where the dependent variable *Business News Heard* takes the value of -2, -1, 0, 1, or 2, depending on how many business news the respondents reported having heard recently (0, 1, or 2), and the sign indicates whether they were positive or negative. This variable has the value 0 if either the respondent did not recall hearing any business news lately, or if one piece of news recalled was positive, and another was negative. Controls include dummies for year-month, age, gender, and marital status. Standard errors are clustered by individual and year-month, and $t-$statistics are shown in parentheses.

Dependent variable	Business News Heard
Income Rank	0.066
	(4.02)
College Degree	0.006
	(0.65)
Recession × Income Rank	-0.252
	(-5.99)
Recession × College Degree	-0.194
	(-6.77)
Observations	188762
Adjusted R^2	0.087

To map this into the model above, we assume that survey respondents are more likely to report having heard a piece of news when the signal s_t is big enough relative to its perceived signal noise. Thus, when low SES individuals underestimate the informativeness of s_t, the perceived news should be dampened compared with the rational Bayesian case (i.e., high SES individuals). In the local thinking case, all distortion is in the prior, but the signal perception is undistorted. Hence, we would expect that there is no difference in news heard between high and low SES individuals. In the confirmation bias case, the signal perception is distorted asymmetrically: low SES individuals should perceive more bad news in good times, but there should be little difference in news perception in bad times.

To check these predictions, we run regressions of the *Business News Heard* variable on our SES variables and their interaction with the NBER recession indicator. The results are reported in Table 11. As the table shows, individuals with higher income perceive more positive business news outside of recessions. The point estimate is also positive for high education, but not statistically significant. However, in recessions, the effect switches sign, and very strongly so: High SES survey respondents report having heard much worse news in recessions. For example, for income rank, the estimated effect in recessions is $0.07 - 0.25 = -0.18$. These results fit well with the misperceived informativeness story, where signal perception is the same on average, but low-SES individuals underreact to the signal in either direction.[14]

These results do not fit as well to the local thinking and confirmation bias theories. In the local thinking theory, there should not be a difference in signal perception. In the confirmation bias story, the wedge in news perception should be big in good times, and very small in bad times. This is not what we find in the above regression.

One caveat to this interpretation is that the news variable might not really capture the signal s_t, but is rather just another way for survey respondents to express their beliefs about the state of the economy. If so, the news variable would capture the same information as the macroeconomic expectations variables. One finding that goes against this alternative view is that, unlike for the macroeconomic expectations, there is no difference in news perception on average between high and low SES individuals.

Another way of seeing this, is to use the news variable as an explanatory variable in the expectations regressions from Table 3. If the news variable captured the same information as the expectations variables, then controlling for the news variable should eliminate the relationship between SES and expectations. The results in Table 12 show that this is not the case. We find that the higher is the value of *Business News Heard*, that is, the more positive economic news people have heard lately, the more optimistic they are when assessing future macroeconomic conditions, which is a natural result. Importantly, however, we continue to find that the respondents' income rank and education remain strong and positive drivers of their macroeconomic optimism. The news variable is therefore not simply a restatement of individuals' macroeconomic expectations.

Interestingly, the cyclicality in the wedge disappears when we control for *Business News Heard*: The coefficients on the interactions with the recession indicator become smaller in magnitude or

[14]Since the number of recession periods is much smaller than the number of non-recession periods, this prediction of no unconditional difference in news perception is also approximately true in our data.

Table 12: Macroeconomic Expectations, Socioeconomic Status, and News Heard

The table presents OLS regressions of macroeconomic expectations on SES measures while controlling for the business news heard by the survey respondents. The variable *Business News Heard* akes the value of -2, -1, 0, 1, or 2, depending on how many business news the respondents reported having heard recently (0, 1, or 2), and the sign indicates whether they were positive or negative. This variable has the value 0 if either the respondent did not recall hearing any business news lately, or if one piece of news recalled was positive, and another was negative. Controls include dummies for year-month, age, gender, and marital status. Standard errors are clustered by individual and year-month, and $t-$statistics are shown in parentheses.

	OPTINDX	PSTK	BUS12	BUS5	BEXP	UNEMP
Income Rank	0.290	0.161	0.298	0.380	0.122	0.131
	(31.13)	(25.25)	(23.30)	(33.24)	(13.72)	(13.85)
College Degree	0.057	0.071	0.019	0.082	0.018	0.028
	(10.56)	(21.84)	(3.10)	(13.53)	(3.64)	(5.55)
Recession $\times$ Income Rank	-0.023	-0.041	-0.182	-0.025	0.134	-0.072
	(-0.84)	(-1.94)	(-5.77)	(-0.84)	(4.55)	(-2.45)
Recession $\times$ College Degree	0.002	-0.007	-0.020	0.008	0.045	-0.024
	(0.16)	(-0.89)	(-1.32)	(0.48)	(3.46)	(-2.15)
Business News Heard	0.210	0.031	0.233	0.167	0.163	0.154
	(76.31)	(24.16)	(68.03)	(47.75)	(58.68)	(58.49)
Observations	188614	56747	172646	177951	185310	187032
Adjusted R^2	0.207	0.128	0.203	0.125	0.114	0.126

statistically insignificant. This is exactly what one would expect according to the misperceived informativeness story. Controlling for the news perception wedge βs_t in (5) absorbs time-variation in the beliefs wedge and leaves a constant bias equal to $\beta\mu_0$. In contrast, in the local thinking story, there shouldn't be a difference in news perception between high and low SES individuals and so controlling for it should not affect the coefficients on the SES variables and their interactions with the recession indicator. This is not what we find. In the confirmation bias story, the bias arises from signal misperception, so controlling for signal misperception should eliminate the entire beliefs wedge, not just the time-varying component (unless one supplements the confirmation bias story with an additional strong pessimistic prior related to SES).

Overall, we view these news-based tests as suggestive that the time-varying pessimism of low-SES individuals likely arises from underweighting of public signals compared with information obtained from one's personal economic environment. But our ability to discriminate between the different behavioral theories based on MSC data is quite limited. For this reason, this conclusion should be viewed as preliminary. While further attempts to discriminate with different data or experiments are beyond the scope of this paper, this seems like an interesting area for future research.

6 Conclusion

Using a sample of more than 180,000 responses from participants in the Michigan Survey of Consumers each month from 1978 to 2014, we show that socioeconomic status (SES) has a strong influence on individuals' beliefs about future macroeconomic conditions such as changes in unemployment, business conditions in general, and stock market performance. Specifically, we find that higher SES individuals—namely, those with higher income and higher education—are more optimistic about future macroeconomic conditions. Moreover, the beliefs wedge between high- and low-SES individuals is strongly pro-cyclical: in recessions, the beliefs wedge almost disappears.

This SES-related heterogeneity in macroeconomic expectations in turn has significant effects on people's economic choices. Specifically, we find that the relative macroeconomic optimism of individuals with higher SES is in part responsible for these households' higher propensity to invest in stocks or to be inclined to purchase homes, cars or durable goods.

We show that the differences in macroeconomic expectations across SES groups could be theoretically predicted by models of belief formation where low-SES individuals either underestimate the informativeness of public signals and as a result underweight them relative to their prior, or are more prone to local thinking, or to confirmation bias, relative to high-SES individuals. The available data do not allow for conclusive tests to assess the relative importance of these possible explanations, but the evidence seems most in line with the mechanism whereby low-SES individuals underestimate the informativeness of public signals about the state of the economy.

Our findings suggest that differences in macroeconomic expectations across people with different socioeconomic standing could potentially contribute to wealth inequality in the population over time, since these expectations influence household decisions such as investing in stocks or in real estate. An interesting avenue for future work is to quantify the importance of divergence in expectations across SES strata for the dynamics of the wealth distribution in the population, possibly by incorporating the SES-related belief heterogeneity in models like those of Piketty (1995), Favilukis (2013), and Gabaix, Lasry, Lions, and Moll (2016). The implications for the wealth distribution are not quite straightforward. For example, while high-SES individuals' beliefs about stock market returns appear to be less biased on average than the more pessimistic beliefs of low-SES individuals, the fact that the optimism about stock returns of high-SES people is more pro-cyclical may imply that they mis-time the stock market, which tends to have counter-cyclical expected returns. We believe that this is a fruitful direction for future research.

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Appendix (for online publication)

A Additional Figures

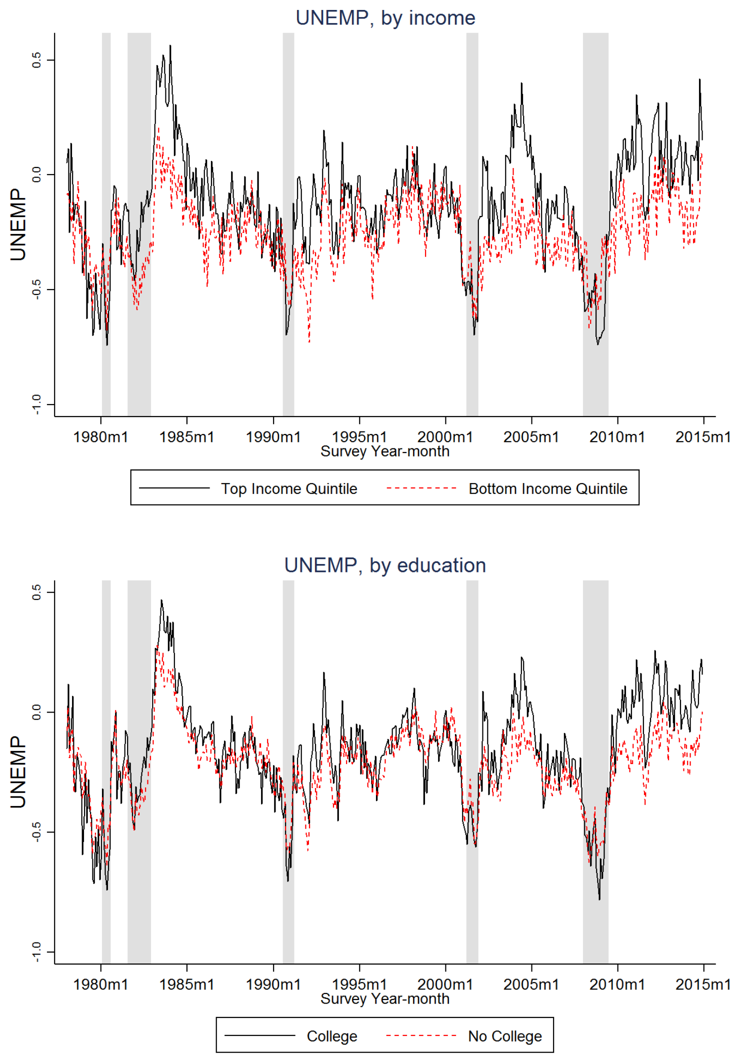


Figure A1: UNEMP by SES, over time

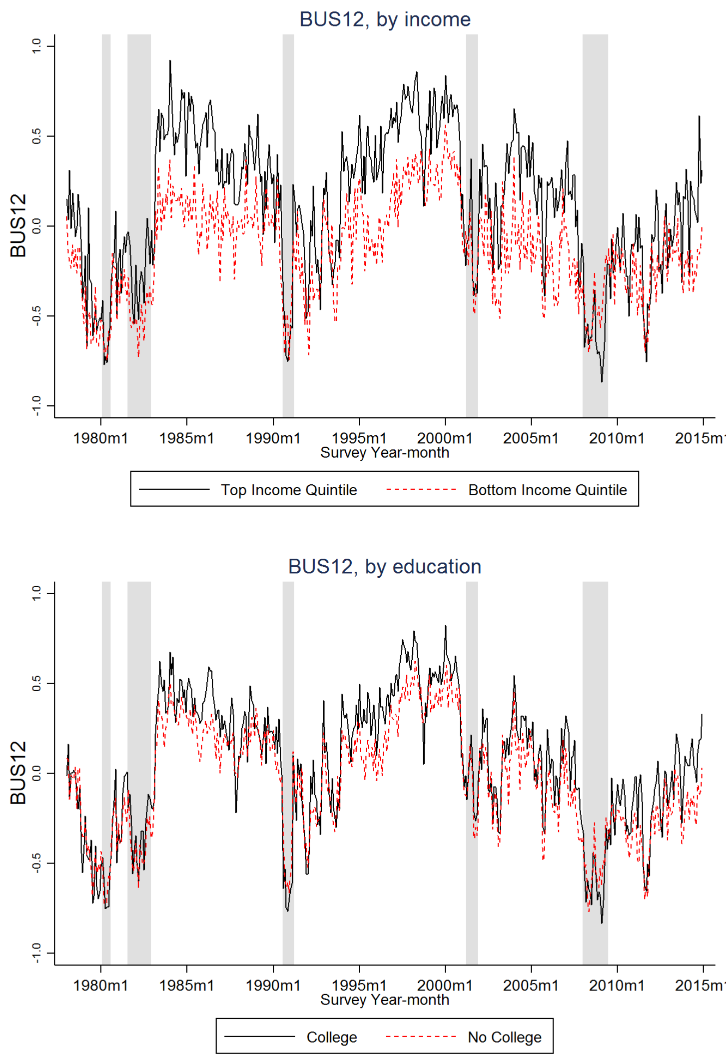


Figure A2: BUS12 by SES, over time

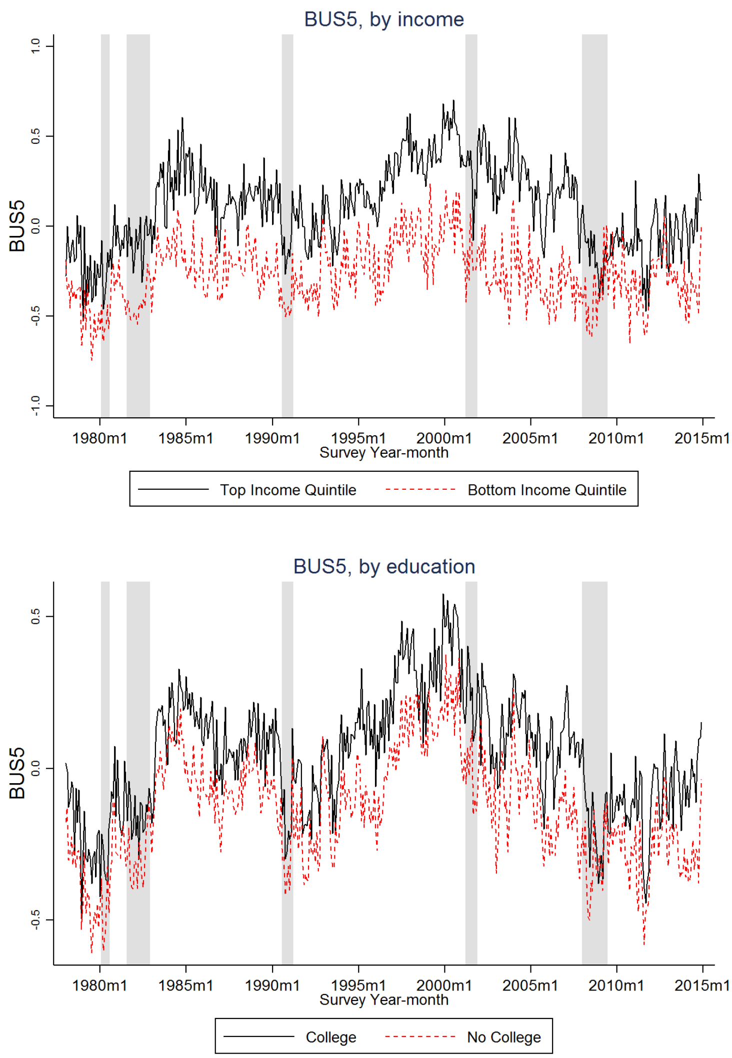
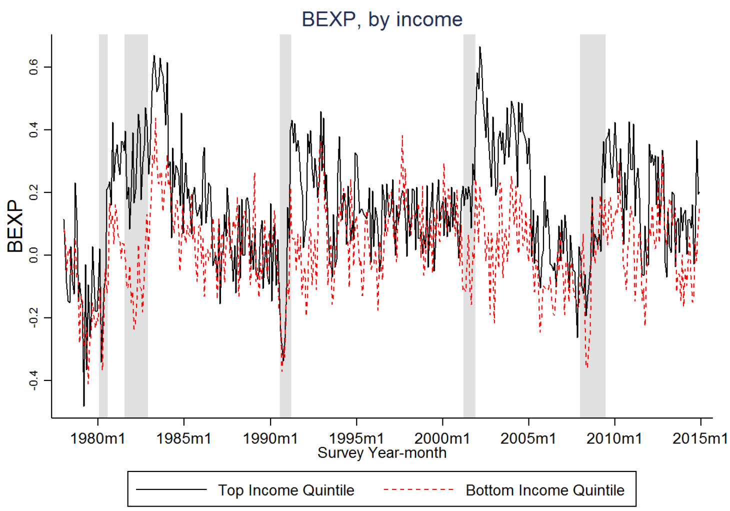


Figure A3: BUS5 by SES, over time



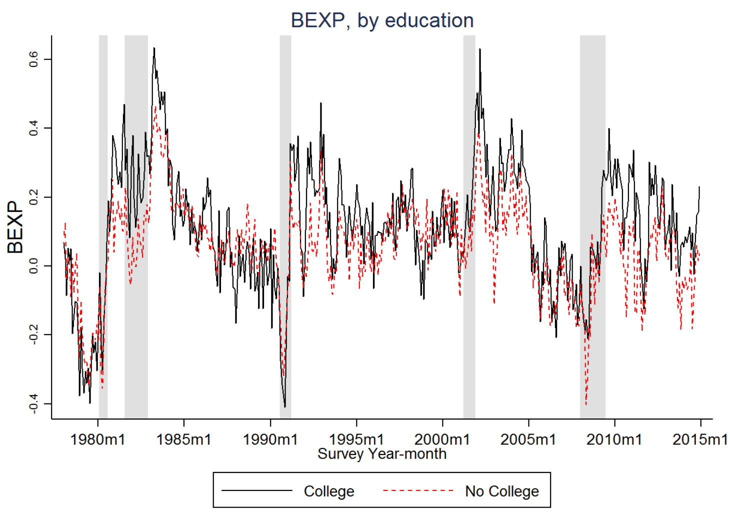


Figure A4: BEXP by SES, over time

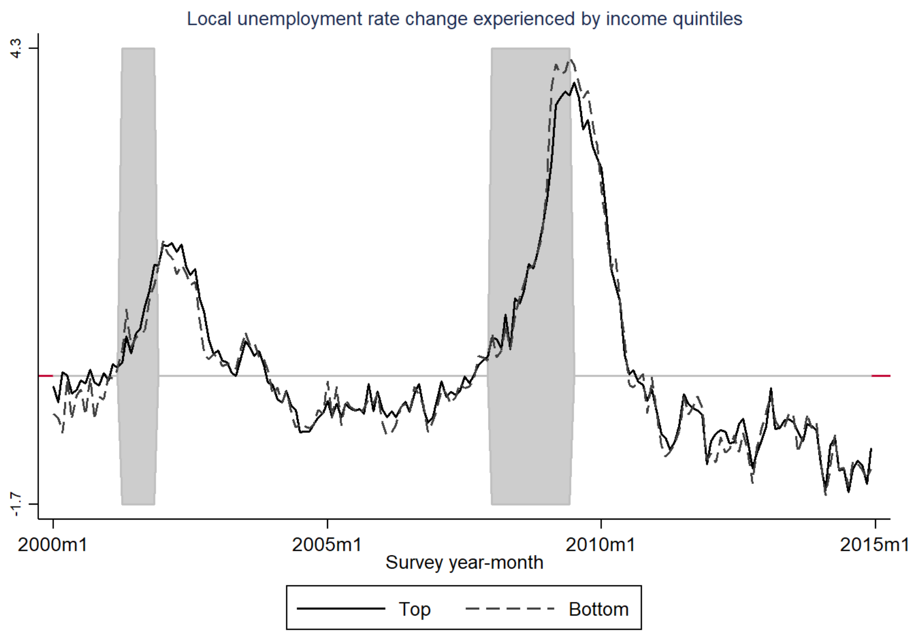


Figure A5: Experienced 12-month local unemployment rate change (lagged)

B Additional Tables

Table A1: OLS regression of macro beliefs on SES using alternative measures of income rank

Percentile income rank, for people in the same 5-year age bin, is based on three alternative definitions of income: the ratio of the respondent's household income to the number of people living in the household (first column), the ratio of household income to the median income in the respondent's county (second column), and the ratio of the household income, adjusted for household size, to the median income in the respondent's county (third column). Controls include dummies for year-month, age, gender, and marital status. Standard errors are clustered by individual and year-month, and $t-$statistics are shown in parentheses.

	OPTINDX	OPTINDX	OPTINDX
College Degree	0.068	0.137	0.145
	(11.39)	(14.70)	(16.22)
Recession × College Degree	-0.032	-0.087	-0.082
	(-2.42)	(-4.21)	(-4.09)
Income Rank(hhsize adj)	0.245		
	(26.14)		
Recession × Income Rank(hhsize adj)	-0.104		
	(-3.67)		
Income Rank(local)		0.279	
		(15.50)	
Recession × Income Rank(local)		-0.173	
		(-3.82)	
Income Rank(local, hhsize adj)			0.221
			(14.60)
Recession × Income Rank(local, hhsize adj)			-0.195
			(-5.05)
Observations	188117	68465	68417
Adjusted R^2	0.112	0.098	0.096

Table A2: SES and macroeconomic expectations: data from first-time responders only

To be conservative when calculating the effects of SES on macroeconomic expectations, we have re-estimated the models in our main analysis in Table 3 in the paper, but only for observations for respondents' first time answering questions in the MSC. Hence, in this subsample, a specific individual appears only one time, and thus clustering standard errors at the person-level is unnecessary. The coefficient estimates in this subsample, as well as the levels of statistical significance, are similar to those in Table 3 in the main manuscript.

	OPTINDX	PSTK	BUS12	BUS5	BEXP	UNEMP
Income Rank	0.287	0.165	0.311	0.377	0.126	0.124
	(22.61)	(20.43)	(19.86)	(27.74)	(10.87)	(9.39)
College Degree	0.058	0.070	0.021	0.085	0.017	0.031
	(8.96)	(17.09)	(2.49)	(12.48)	(2.82)	(4.96)
Recession × Income Rank	-0.090	-0.063	-0.272	-0.054	0.078	-0.118
	(-2.73)	(-3.18)	(-7.56)	(-1.73)	(2.21)	(-3.58)
Recession × College Degree	-0.053	-0.012	-0.067	-0.031	-0.008	-0.071
	(-3.64)	(-1.33)	(-3.47)	(-1.79)	(-0.49)	(-5.29)
Observations	117613	33329	107058	110387	115218	116442
Adjusted R^2	0.113	0.111	0.129	0.080	0.053	0.068

Table A3: Within-individual effects of SES on expectations.

The table presents OLS regressions of within-individual changes in macroeconomic expectations between the the first and the second time the individual participated in the MSC on within-individual changes measured over the same six-month window in the value of *1-Yr Change in Personal Situation*. Year-month dummies are included. Standard errors are clustered by year-month.

	OPTINDX	PSTK	BUS12	BUS5	BEXP	UNEMP
Personal Condition change	0.0451	0.0072	0.0765	0.0435	0.0101	0.0312
	(13.53)	(2.96)	(14.41)	(9.33)	(2.65)	(8.07)
Observations	72472	22126	61446	65202	70179	71395
Adjusted R^2	0.065	0.020	0.060	0.019	0.027	0.034

Table A4: Macroeconomic Expectations, SES, and Household Choices

The table presents the first stage results for each IV regression shown in Table 7 in the main text where the dependent variable is a measure of investment choices or attitudes to consumption decisions (*Invest*, *Invest Share*, *HOM*, *DUR*, *CAR*), using solely the panel sub-sample, that is, observations from the same individual, acquired six months apart. The macroeconomic expectations index *OPTINDX* is instrumented with *lagged OPTINDX*. *Invest*: Indicator for investment in equities; *Invest Share*: Log(Amt Invested/Income); *HOM*: Home buying attitude; *DUR*: Durables buying attitude; *CAR*: Car buying attitude. Controls include dummies for year-month, age, gender, and marital status. Standard errors are clustered by year-month, and $t-$statistics are shown in parentheses.

	Observations for which *Invest* is available	Observations for which *Invest Share* is available	Observations for which *HOM* is available	Observations for which *DUR* is available	Observations for which *CAR* is available
Dependent variable			OPTINDX		
Lagged OPTINDX	0.532	0.538	0.482	0.481	0.483
	(69.58)	(57.75)	(91.83)	(90.67)	(91.27)
Income Rank	0.153	0.116	0.172	0.174	0.171
	(9.24)	(5.33)	(15.87)	(15.62)	(15.48)
College Degree	0.045	0.044	0.026	0.024	0.026
	(5.31)	(4.27)	(4.18)	(3.92)	(4.30)
Observations	32143	18226	68492	66511	66540
Adjusted R^2	0.373	0.380	0.328	0.328	0.330

Table A5: Effects of within-person changes in expectations on within-person changes in choices

OLS regressions of within-individual change in (possible) action on within-individual change in income rank and OPTINDX. Year-month dummies are included. Standard errors are clustered by year-month.

	Invest	Invest Share	HOM	DUR	CAR	ln(Invest Amt)
OPTINDX change	0.008	0.043	0.098	0.107	0.106	0.046
	(2.34)	(3.42)	(17.38)	(14.99)	(15.01)	(3.60)
Income Rank change	0.092	-1.608	0.025	0.079	0.057	0.723
	(4.36)	(-17.43)	(0.85)	(2.65)	(1.65)	(8.07)
Observations	28670	13898	65373	61500	61766	13898
Adjusted R^2	0.006	0.054	0.037	0.024	0.020	0.022

Table A6: Macroeconomic Expectations, SES, and Household Choices

The table presents the first stage results for each IV regression shown in Table 9 in the main text where the dependent variable is a measure of investment choice ($Invest$ or $Invest\ Share$), using solely the panel sub-sample, that is, observations from the same individual, acquired six months apart. The stock market belief variable $PSTK$ is instrumented with *lagged* $PSTK$. *Invest*: Indicator for investment in equities; $InvestShare$: Log(Amt Invested/Income). Controls include dummies for year-month, age, gender, and marital status. Standard errors are clustered by year-month, and $t-$statistics are shown in parentheses.

	Observations for which *Invest* is available	Observations for which *Invest Share* is available
Dependent variable	PSTK	
Lagged PSTK	0.372	0.361
	(50.36)	(39.39)
Income Rank	0.103	0.075
	(11.45)	(6.94)
College Degree	0.048	0.045
	(11.25)	(8.57)
Observations	21400	13500
Adjusted R^2	0.247	0.225

Table A7: Effects of PSTK and SES on investment decisions for panel respondents split by education level.

This table presents the same analysis as in Table 9 in the manuscript, but separately for individuals with a college education (i.e., high SES respondents) in columns 1-3, and for those without a college education (i.e., low SES respondents) in columns 4-6. The effects of $PSTK$ on the choice to participate in equity markets ($Invest$) and on the size of equity exposure relative to income ($Invest\ Share$) are similar across the two categories of respondents.

	PSTK	Invest	Invest Share	PSTK	Invest	Invest Share
	College educated (High SES)			Not college educated (Low SES)		
Income Rank	0.178	0.782	-0.015	0.133	0.432	0.446
	(14.46)	(39.95)	(-0.17)	(10.13)	(20.78)	(5.21)
PSTK		0.419	1.221		0.415	1.303
		(9.81)	(6.94)		(11.09)	(7.79)
Observations	12484	11498	6096	10535	9902	7404
Adjusted R^2	0.085	0.223	0.184	0.091	0.132	0.242

C Relative Attenuation Bias in Levels and Differences Specifications

Suppose the true data generating process of the macroeconomic belief, y, of individual i at time t is given by the following:

$$y_{i,t} = \beta x^*_{i,t} + \epsilon_{i,t}, \tag{1}$$

where $x^*_{i,t}$ is the true SES of individual i at time t and $\epsilon_{i,t}$ is IID with variance σ^2. We assume that true SES is persistent:

$$x^*_{i,t} = \alpha x^*_{i,t-1} + \eta_{i,t}. \tag{2}$$

where $\eta_{i,t}$ is IID with variance σ^2_η. Let x be the empirically measured SES, where

$$x_{i,t} = x^*_{i,t} + e_{i,t}, \tag{3}$$

and $e_{i,t}$ represents measurement error with

$$e_{i,t} = u_i + \xi_{i,t}, \tag{4}$$

where $\xi_{i,t}$ is IID with variance σ^2_ξ and u_i is an IID individual-specific fixed effect with variance σ^2_u. It seems plausible that many sources of survey response error due to imperfect recall or lack of attention represent draws of errors that are uncorrelated across survey waves. But one could also imagine that some components are persistent. The fixed effect is meant to capture such persistent components u_i.

Consider first an OLS regression in levels of y on x. The population slope coefficient is

$$b_{\text{level}} = \beta \frac{\text{var}(x^*_{i,t})}{\text{var}(x_{i,t})} = \beta \frac{\sigma^2_{x^*}}{\sigma^2_{x^*} + \sigma^2_\xi + \sigma^2_u}, \tag{5}$$

where $\sigma^2_{x^*_{i,t}} = \text{var}(x^*) = \sigma^2_\eta/(1-\alpha^2)$. Thus, we get the standard attenuation bias, $b < \beta$ due to measurement error if $\sigma^2_e > 0$.

Now consider a regression in first differences of $\Delta y_{i,t} \equiv y_{i,t} - y_{i,t-1}$ on $\Delta x_{i,t} \equiv x_{i,t} - x_{i,t-1}$. In this case, the population regression coefficient is

$$b_{\text{diff}} = \beta \frac{\text{var}(\Delta x^*_{i,t})}{\text{var}(\Delta x_{i,t})} = \beta \frac{\sigma^2_{x^*}}{\sigma^2_{x^*} + \frac{\sigma^2_\xi}{1-\alpha}}. \tag{6}$$

Differencing removes u_i and therefore this component of the measurement error does not contribute to the attenuation bias in the differences specification. But the contribution of ξ is now magnified if $\alpha > 0$, because differencing removes much of the persistent true variation, but leaves the uncorrelated component of the measurement error in the observed difference $\Delta x_{i,t}$. As a consequence, the attenuation bias can be much bigger in the differences specification.

There is very little existing evidence in the literature on the dynamic properties of survey response error. However, a recent paper by Hyslop and Townsend (2018) compares annual individual earnings reported in survey panel data with matched administrative data in New Zealand. They use a dynamic measurement error model to estimate the two variance ratios $\text{var}(x^*_{i,t})/\text{var}(x_{i,t})$ and

$\text{var}(\Delta x^*_{i,t})/\text{var}(\Delta x_{i,t})$ that, according to the relations discussed above, pin down the ratio $b_{\text{diff}}/b_{\text{level}}$ that we are interested in. In their data, however, $\Delta x_{i,t}$ and $\Delta x^*_{i,t}$ are measured over non-overlapping annual windows. In our MSC panel, respondents are asked about their income over the past year in two surveys spaced six month apart, i.e., income is measured over overlapping periods. Therefore, the moments of income changes in our data, and hence the measurement error properties, are not directly comparable to their estimates.

For this reason, we simulate the model above, with shocks drawn from normal distributions, at a semi-annual frequency for given values of α, σ_u^2, and σ_ξ^2. We can normalize the model by setting $\sigma_\eta^2 = 1$ without effect on the variance ratios and attenuation bias that we are interested in. We then time-aggregate the simulated semi-annual series of x and x^* to annual numbers. We then look for values of α, σ_u^2, and σ_ξ^2 that allow us to match three moments: the autocorrelation of income changes in the MSC measured over yearly windows with six month overlap (0.87), and the variance ratios $\text{var}(x^*_{i,t})/\text{var}(x_{i,t})$, and $\text{var}(\Delta x^*_{i,t})/\text{var}(\Delta x_{i,t})$ in Hyslop and Townsend's non-overlapping annual data.

Hyslop and Townsend (Table 7) report, for males, an estimate of 0.261 for $\text{var}(\Delta x^*_{i,t})/\text{var}(\Delta x_{i,t})$. For $\text{var}(x^*_{i,t})/\text{var}(x_{i,t})$, their approach can only pin down a lower bound estimate, which is 0.560. Using this lower bound in our calibration means that we obtain an upper bound on the coefficient ratio $b_{\text{diff}}/b_{\text{level}}$. We exactly match these empirical moments by setting $\alpha = 0.92$, $\sigma_u^2 = 1.29$, and $\sigma_\xi^2 = 4.14$ in our simulations, which yields an upper bound on the coefficient ratio of $b_{\text{diff}}/b_{\text{level}} \leq 0.29$ which is roughly the magnitude of the ratio of estimated coefficients of that we observe in Tables 3 and 5 in the main text of the paper (for OPTINX the ratio is 0.24). Thus, an empirically plausible amount of measurement error in SES can account for the differences in coefficient estimates between the levels and differences specifications. (If we use Hyslop and Townsend's estimates of the variance ratios for females, for whom measurement error is generally lower, we get a somewhat higher upper bound of $b_{\text{diff}}/b_{\text{level}} \leq 0.47$, but given that this is an upper bound, even this estimate would suggest that measurement error accounts for much of the difference in the levels and differences estimates we obtain).