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AI and Economic Transition | North America

Dispelling an AI Myth: Why Affluent Consumers May Be Safer Than Advertised

High-income, college-educated, urban households are most exposed to AI displacement but also to potential AI gains: productivity-driven wage growth, job creation, wealth effects, and disinflation. We think these upside channels are underappreciated. In our base case, these consumers benefit most on net, but rapid diffusion is a key risk.

AlphaWise α

Key Takeaways

- AI will affect consumers simultaneously through several channels, with labor markets, asset markets, and prices all playing key roles. Exposure to each of these varies widely across demographic groups.
- For college-educated, high-income, city-dwelling ("CHIC") households, elevated equity wealth relative to labor income makes asset markets an important driver of spending. Relatively modest increases in asset markets can offset the spending effects of temporary declines in labor income.
- Career stage is critical to understanding overall risks. Established CHIC workers likely have greater exposure to augmentation and wealth offsets, while younger consumers may be more vulnerable to displacement. Given that this younger cohort accounts for less spending, the near-term drag on aggregate consumption is likely smaller.
- In our base case for AI and economic transition, task creation and wealth effects offset labor displacement, resulting in an increase in output and income. CHIC households reap the largest gains, and income and wealth inequality widen.
- In our bear case, rapid diffusion leads to higher unemployment, with more extreme outcomes when accompanied by asset market declines. CHIC households are first affected by displacement, but the resulting aggregate demand shock spreads the weakness across cohorts, and monetary and fiscal policy responses will be key.

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Executive Summary

Key takeaway: In our base case outlook for AI adoption and economic transition, AI boosts productivity without a large rise in unemployment, as task creation and wealth effects are offsets to labor market disruption. In this outcome, we expect AI to disproportionately benefit college-educated, high-income, city-dwelling ("CHIC") households over the longer run, a contrary view to the conventional wisdom that white-collar households are the most AI-vulnerable cohort. This is based on our findings across three key channels:

Labor markets: CHIC workers have high occupational exposure to AI. This brings risk but also opportunity; these workers are exposed to displacement, but also to productivity gains and new jobs.

Wealth: CHIC households, and particularly older CHIC households, have greater equity exposure, resulting in larger spending impacts for these households from AI-driven gains in capital returns.

Inflation: CHIC households are more exposed to longer run AI-driven disinflation in services and less exposed to potential near term AI-related inflation pressures.

Importantly, among CHIC households, outcomes likely vary by career stage. Established, older professionals may be well positioned to capture AI-related productivity and asset-price gains. Highly-educated younger professionals may be more vulnerable, as AI may substitute for entry-level tasks with less offset from wealth. These distinctions matter for macroeconomic transmission: weakness among younger entrants would likely have a smaller effect on aggregate consumption than a comparable disruption among established households who account for a large share of spending. Overall, AI could weaken career formation without adversely affecting the CHIC cohort as a whole, widening income and wealth inequality over time, much as the internet and digital innovation wave did.

Conventional discussions of the effects of AI on different cohorts of consumers have focused primarily on occupational exposure, often culminating in a fear of white-collar job loss. This is only one part of the story. We broaden the analysis to three channels through which AI can affect consumer spending: labor markets, financial wealth, and inflation. Across demographic groups, consumer exposures to each of these will vary.

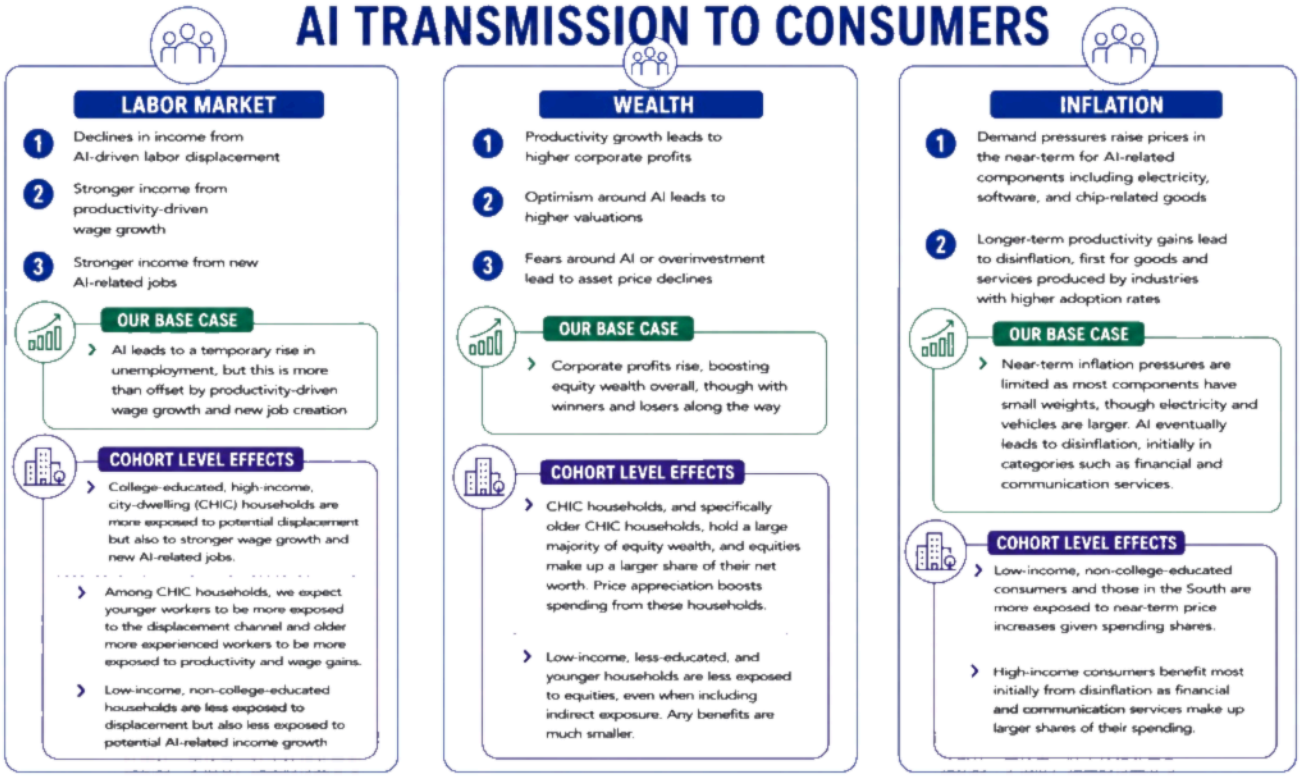
AI "exposure" is not inherently positive or negative. Greater occupational exposure, for example, could mean greater risk of displacement or larger income gains from productivity-driven wage growth. As this is the fifth note in our AI and Economic Transition series, we build off results of our prior work. In our last note, we used a general equilibrium model to form base and bear case outlooks around AI. Our base case assumes AI diffuses twice as fast as the internet and digital age. In this scenario, AI boosts productivity without triggering a downturn; a temporary rise in unemployment is offset by real wage gains and new job creation, resulting in output and income gains. Our bear case

assumes adoption much faster than any historical precedent. This leads to higher unemployment, reflecting skill mismatches and demand-side weakness. In the data so far, our work on AI and labor market disruption finds that AI is causing some excess unemployment in occupations with high AI exposure (typically white collar professions with computer-facing tasks), but effects remain relatively small.

In this note, we extend the analysis to refine our base and bear case outcomes by including outlooks for consumers across four demographic factors: income, education, region, and age. While our prior work provides a baseline for the economy and monitors the incoming data against this view, it does not speak directly to differential effects across consumers. Using micro data on occupations, consumer balance sheets, and spending patterns, we examine exposures of each cohort across the three transmission channels, which in turn helps us develop base and bear case expectations for each.

Cohort Exposures Across Each Channel

Exhibit 1: Overview of AI Transmission to Consumers Across our 3 Key Channels



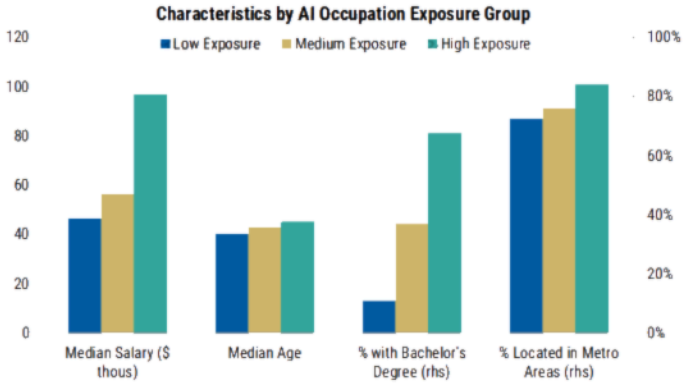
Source: Morgan Stanley Research

The first transmission channel we assess is labor markets: Occupational exposure can lead to declines in income through displacement, or gains through productivity-driven wage growth and new job creation.

Using a framework that assesses how tasks within each occupation align with AI capabilities, we find that high AI exposure occupations tend to be concentrated amongst higher-income, highly-educated, city-dwelling (or "CHIC") households. Within this group, younger CHIC workers are so far more affected by displacement, while for more experienced workers, exposure could mean "augmentation" and thus faster productivity

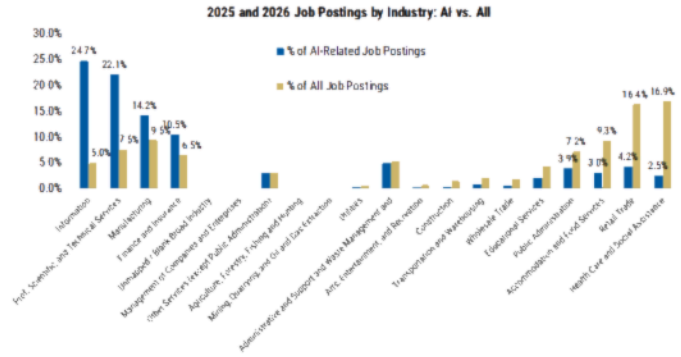
and wage growth. In terms of job creation, it is still early, but new AI-related occupations have so far been aimed at these same CHIC consumers; AI-related job postings have been targeted towards higher-income consumers with some experience in similar "highly-exposed" industries.

Exhibit 2: High exposure AI occupations tend to be higher-income, more educated and concentrated in cities



Source: IPUMS, Morgan Stanley Research

Exhibit 3: Industries more exposed to AI such as professional services, information services, and finance account for a larger share of AI-related job postings



Source: AlphaWise, Lin-Up, Morgan Stanley Research

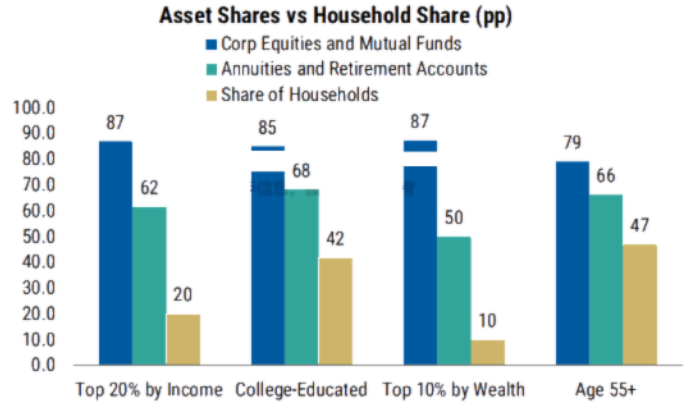
The second transmission channel is through financial wealth: Higher corporate profits or valuations from AI could lead to wealth gains, but with the risk that AI-related overinvestment could bring a downturn.

CHIC households, and especially older CHIC households, have more equity exposure, both in absolute terms and as a share of their own net worth. The top 20% income cohort, the college-educated group, and the 55+ age group all account for around 80+% of equity exposure among households. Among lower-income and less-educated households, a smaller share have any equity exposure at all. As a result, changes in equity valuations can more easily drive changes in net worth, and thus changes in spending, for CHIC households.

The final transmission channel we consider is through inflation: Near-term demand pressures from AI could lead to higher prices, but in the longer-term, productivity gains could result in disinflation.

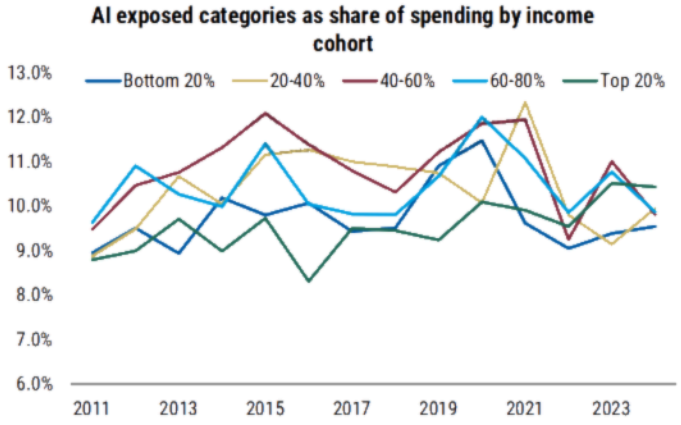
We expect electricity, software, and chip-related goods to drive near-term AI-related price pressures, even if those pressures are somewhat limited. Given these categories (especially electricity) make up larger shares of spending for low-income, less-educated, and younger households, these groups are likely more exposed. Meanwhile, if longer-term disinflation first stems from industries with higher adoption rates, and thus materializes in services categories such as financial and communication services, higher-income households will benefit first.

Exhibit 4: Both direct equity holdings and retirement accounts are much more concentrated among high-income, high-wealth, college-educated, and older households



Note: As of 4Q25. Source: Federal Reserve Board, Haver Analytics, Morgan Stanley Research

Exhibit 5: Exposure to categories with potential near term AI price pressures is similar across income cohorts, but low-income are more exposed to electricity and high-income to vehicles



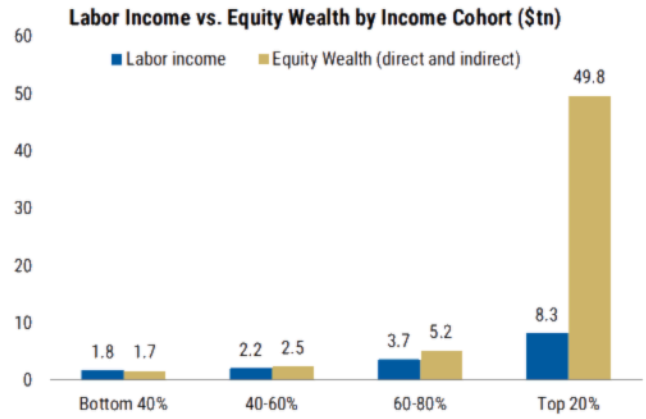
Note: Here "AI exposed categories" include electricity, vehicles, computers, telephones, computer software, video game hardware and accessories, and major appliances. Source: B. S. Hayer Analytics, Morgan Stanley Research

Combining these findings, CHIC households are more exposed to labor displacement, but also to AI's potential upside: productivity-driven wage growth, new job creation, wealth effects, and disinflation. Lower-income, less-educated consumers are at less risk of displacement, but face more near-term price pressures and stand to benefit less from AI-related job and wealth creation.

Net Effects: CHIC households benefit most in the base case as wealth effects and task creation offset labor displacement

The next question is how these exposures will balance out. As described above, our base case is that AI will raise productivity, and positive effects from wage growth, task creation, and wealth effects will offset the rise in unemployment. In this scenario, we expect CHIC households to benefit most. Some high-income, highly-educated workers may face temporary periods of softer consumption, especially younger workers that likely have greater risk of displacement and lower accumulated equity wealth. That said, for this group's spending as a whole, substantial levels of equity wealth relative to labor income mean that relatively modest gains in asset prices can offset the spending effects of declines in labor income. In our base case, CHIC households are best off, reaping the largest gains from financial asset appreciation and also from eventual wage gains and disinflation.

Exhibit 6: For high-income consumers, equity wealth is very elevated relative to labor income



Source: BLS, Federal Reserve Board, Haver Analytics, Morgan Stanley Research

While income and wealth inequality widen in this scenario, it does not mean low-income or less-educated consumers are worse off in absolute terms. These consumers could benefit from eventual broadening out in wage gains and disinflation, or from monetary easing that may accompany any initial displacement.

In our bear case, recession-like outcomes are possible as rapid AI diffusion means job creation cannot keep up with job displacement. In this scenario, we expect CHIC households to experience the initial adverse effects because of their greater occupational exposure. If displacement is accompanied by asset market declines, the downturn would be much more extreme. Given these households control a large share of total spending, weaker demand would ultimately spread the shock across the broader economy. The initial intuition might be that white-collar workers would be most affected, but the net effect, in our view, would be worse outcomes for all cohorts. The ultimate distributional effects would depend not only on the pace of AI adoption and asset market outcomes, but also on monetary and fiscal policy responses.

Setting the Stage: Our Framework and Assumptions

Grounding in our Prior Work: Our Base Case for AI

For this analysis, we build off the results of our prior work on AI and Economic Transition. In our recent note, we used a general-equilibrium framework to assess potential labor market outcomes of AI. In doing so, we found the amount of AI disruption is largely dependent on three forces: 1) the speed of AI adoption, 2) the speed and quantity of new task creation, and 3) indirect feedback loops such as wealth effects.

These results are intuitive. Slower diffusion gives workers more time to adapt, faster task creation creates new employment opportunities, and stronger asset markets support demand, and in turn, labor demand. As a result, assuming faster diffusion or excluding offsets from task creation and wealth effects leads to much more extreme conclusions.

In our "base case", we assume a moderate speed of diffusion, which is still 2x that of the Internet (e.g. AI diffuses in about a decade versus two previously). We link the pace of task creation to the speed of diffusion and assume wealth effects that are smaller than those observed historically, to be conservative.

In this scenario, the outcome is relatively optimistic; AI boosts productivity without triggering a downturn. While there is some temporary labor displacement, with the unemployment rate rising by around 0.5pp at the peak, real wage growth accelerates, employment is rebalanced across occupations, productivity supports disinflation, and profits rise. The net outcome is faster output and income growth.

Our "bear case" is based on a scenario of rapid AI diffusion, in which full adoption takes only six years, much faster than any historical precedent. Here, recession-like outcomes are possible as fast adoption means job displacement far outweighs job creation in the short term. Dependent on the size of wealth effects assumed, the unemployment rate rises by anywhere from 0.6pp - 4.1pp at its peak. The increase in unemployment is due to two drivers: 1) a mismatch in skills between workers and available jobs, and 2) demand-side weakness after the initial employment shock.

AI and Economic Transition

For more perspectives on how AI will affect the economy, please see our prior notes: **1)** Lessons from the Five Innovation Waves that Preceded AI, **2)** AI Labor Disruption: Still Modest but Increasingly Visible, **3)** Industries with high AI exposure are seeing labor productivity from faster output growth, not labor displacement, **4)** Expect Rhyme, Not Rupture, The Pace of AI Adoption, Productivity Gains, and Labor Displacement Risks, **5)** Building a better mousetrap: AI spending and its contribution to US GDP growth

Demographics Lead to Divergences

While the above model helps us develop an aggregate base case scenario, the model

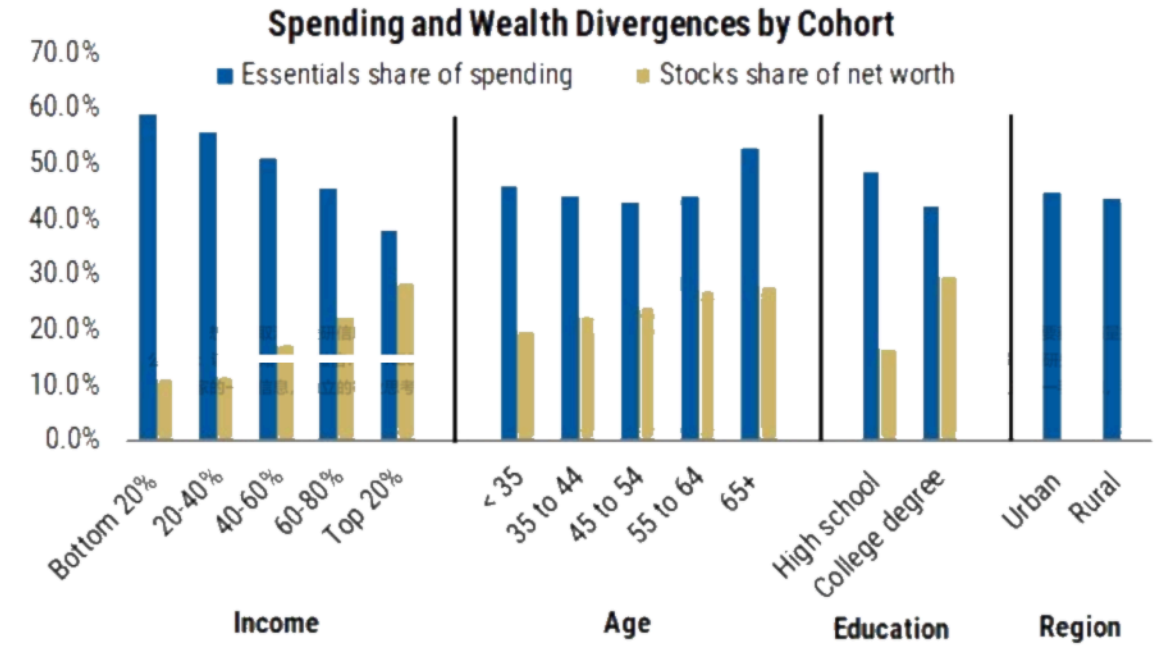
assumes a "representative household". It therefore does not capture the behaviors and outcomes of different cohorts of consumers.

Consumer subgroups differ in the types of work they do, their levels of income and wealth, their responses to changes in the economic backdrop, and the goods and services they purchase. As a result, the effects of AI will not be uniform. **In this note, we focus on differential effects across four demographic factors: income, education, region, and age.**

In each section, we show as much detail as the data allow, but we cannot break down every channel of exposure across all demographic subgroups. That said, we find some common threads: the exposures and potential outcomes for college-educated, high-income, city-dwelling consumers, which we refer to as "CHIC" households, tend to be similar. Meanwhile, the effects for low-income, non-college-educated, and rural consumers tend to be similar. This makes sense given the overlap among these groups. CHIC households tend to work white-collar jobs, are more sensitive to asset market moves, and spend relatively more on discretionary services and big-ticket items. Meanwhile, the opposite is true for the second group; these households are more dependent on labor market income and spend relatively more on essentials (Exhibit 7).

Further distinction comes when we include age. Within our CHIC group, we expect different outcomes for older, more experienced workers versus younger workers. First, while the labor market exposures of two individuals in the same occupation will appear the same, in reality tasks likely differ by career stage. Wealth levels also vary greatly by age, even for consumers with similar income and education levels, as do spending patterns.

Exhibit 7: Spending and wealth divergences by income cohort, age group, education level, and region



Note: Stock share of net worth is not available for regional groups. Source: BLS, Federal Reserve Board, Haver Analytics, Morgan Stanley Research

To organize our analysis, we focus on three key transmission channels, each of which plays an important role in the general equilibrium model: [1]

1) **Labor markets.** AI can affect labor markets in several ways. First, it could be possible that some tasks are cheaper to perform with AI rather than human labor, and if so, this could lead to labor displacement. Second, AI could enhance consumers' productivity, allowing them to produce more output with the same number of hours worked. If so, this could lead to stronger wage growth. Third, new tasks and jobs could be created related to AI, increasing employment in certain industries or creating new industries entirely.

For consumers: The net effect of these three forces will determine total labor income, the main driver of spending. If the income lost due to labor displacement is larger than the income gained from productivity-driven wage growth and new jobs, then labor income will decline, but the opposite could be true as well.

2) **Wealth.** If AI boosts productivity, firms may produce the same output at a lower cost, increasing profits. Even before profits rise, optimism around AI could lift valuations. In a bear scenario, fears around AI or overinvestment could result in asset price declines.

For consumers: If corporate profits or valuations rise, consumers with equity exposure (either directly or through retirement accounts) will experience increases in wealth. Studies have shown that when a consumer's wealth rises, their spending typically does as well; it is estimated that for every dollar increase in permanent wealth, consumers typically spend 3-5 cents more.

3) **Inflation.** AI's effect on inflation is likely two-fold. In the near term, increased demand for electricity, software, and chip-related goods (phones, tv, household appliances, and cars) could result in larger price increases. In the medium to longer term, productivity gains could lower production costs, slowing inflation or even reducing prices.

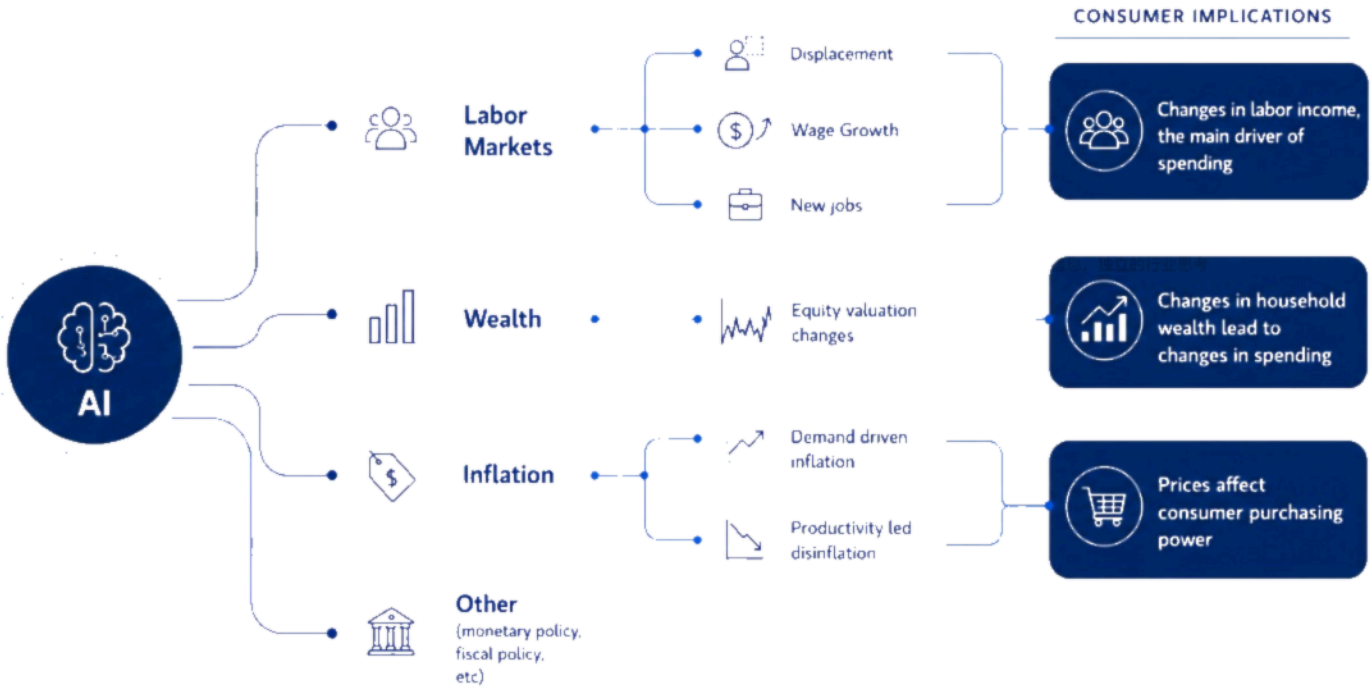
For consumers: Higher prices in the near term can weigh on consumer purchasing power, reducing the quantity of goods and services consumers can buy. In the longer term, disinflation could have the opposite effect. For consumption, we typically compare income growth vs. inflation: if income growth is outpacing inflation, consumers have more purchasing power.

The next three sections dive into each of these channels, and the exposures of each demographic group, in more detail.

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1. These three are not the only transmission channels. Changes in labor markets and inflation could lead to changes in monetary and fiscal policy, which can further affect spending. Agentic commerce can change the way consumers shop, or which items they decide to buy. AI developments in mortgages or other consumer debt products can help facilitate debt consolidation and personal finance decisions. All of these can affect consumer balance sheets and spending, but for this analysis we limit our focus to these three primary channels.

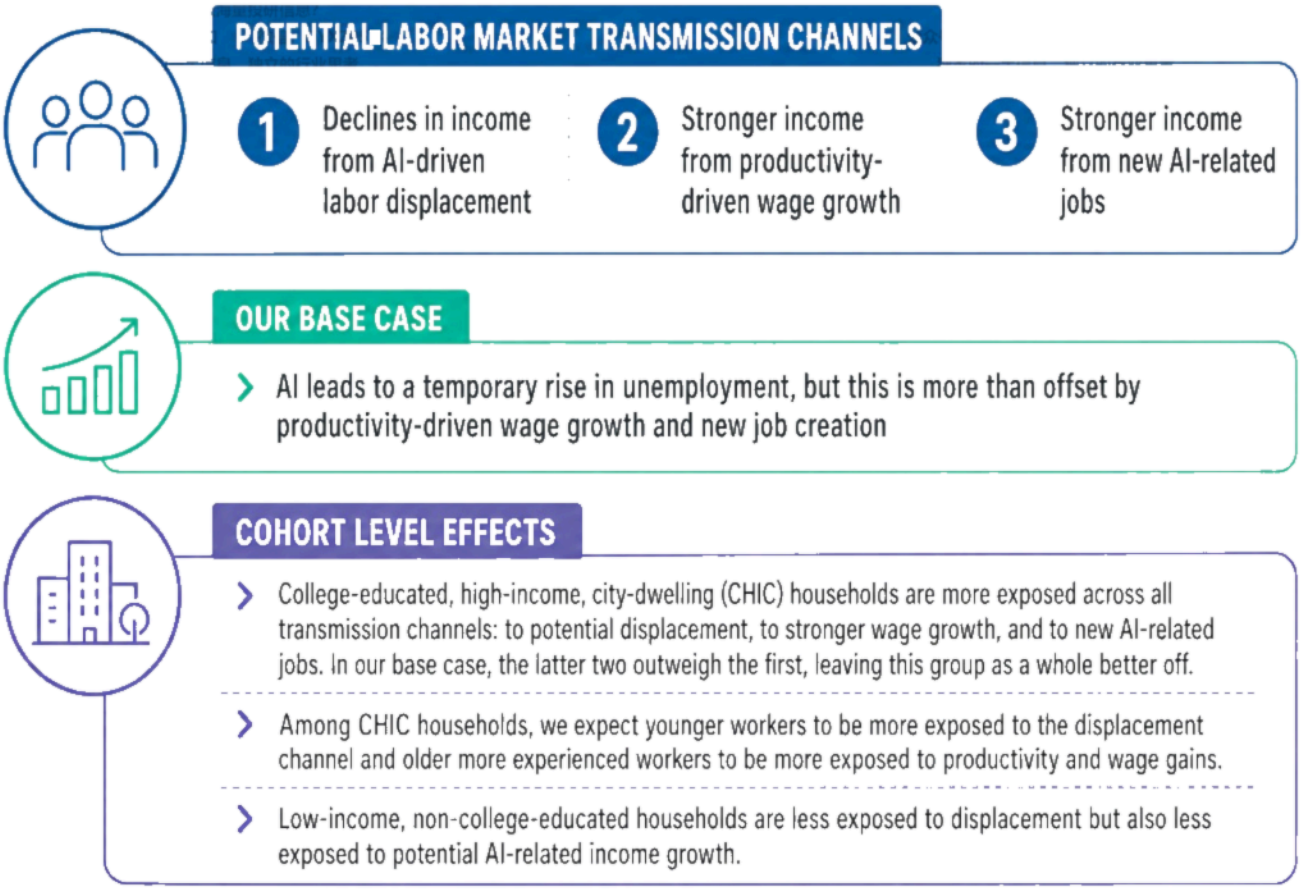
Exhibit 8: Key transmission channels of AI to consumers



Source: Morgan Stanley Research

Labor Markets: CHIC households are most exposed to job losses...and job gains

Exhibit 9: Potential Labor Market Transmission Channels of AI

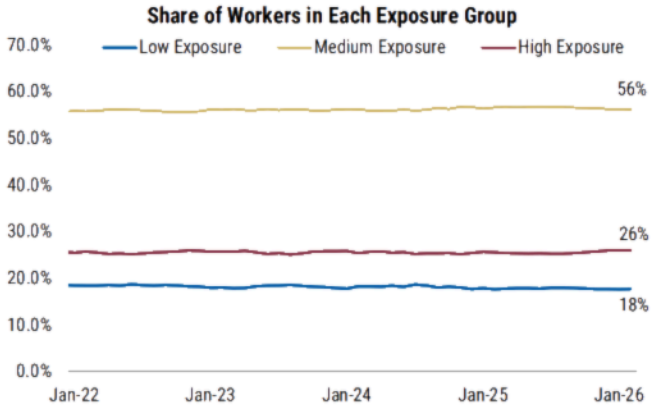


Source: Morgan Stanley Research

Occupational Exposures by Cohort

We first look at which consumers are most exposed to AI in their occupations. To do so, we define occupational exposure based on a framework developed by Felten et al. (2021). Felten and co-authors construct an AI exposure index by assessing how tasks and abilities within each occupation align with current and anticipated AI capabilities. For example, an accountant may perform tasks related to classification and document recognition, which AI is likely capable of. After mapping AI capabilities to the tasks within each occupation, the exposure score is calculated as a weighted average.

Exhibit 10: Share of workers in each exposure group over time, among all workers



Source IPUMS, BLS, Morgan Stanley Research

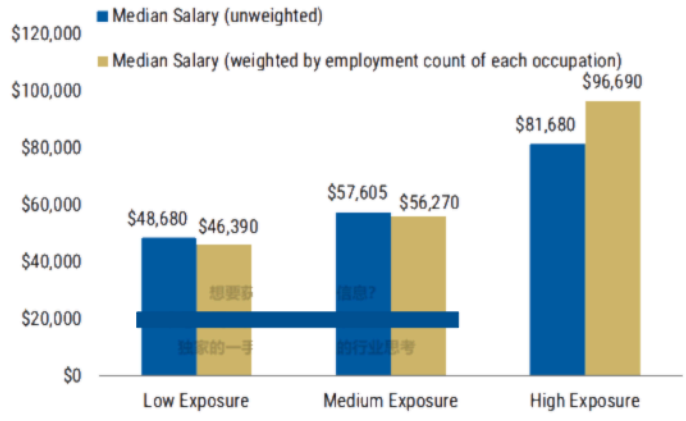
We group occupations into three categories based on their exposure values: the bottom 25% of exposure scores are considered "low exposure", the middle 50% are "medium exposure", and the top 25% are "high exposure." Because occupation sizes differ, workers are not distributed 25/50/25 across the three groups: about 18% of workers are in "low exposure" occupations, 56% are "medium exposure", and 26% are "high exposure" (Exhibit 10).

The occupations within each grouping are largely intuitive: high exposure occupations are typically white collar jobs involving information processing, quantitative analysis, and standardized decision making, while low exposure occupations are predominantly blue collar jobs that rely heavily on human presence, physical work, and dexterity. Importantly, this indicates only measured exposure, which can lead to either automation or augmentation; AI could either replace a task or enhance a worker's productivity in performing it.

We first examine exposure by income cohort. To do so, we use the median annual salary by occupation from the most recently available data, which is as of 2024. As seen in Exhibit 12 , there is a positive correlation between AI exposure rate and income; the higher the occupation's income, the higher the AI exposure rate tends to be.

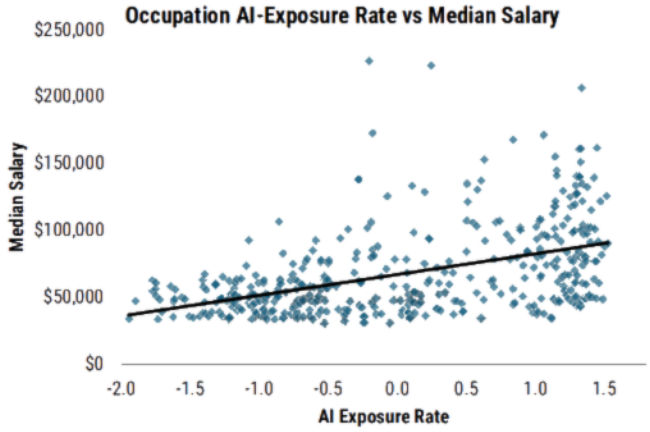
Our low exposure group had a median annual income of $46k while the high exposure group that had median income of $97k (Exhibit 11). This implies the median worker in low exposure occupations was around the 30th percentile of income, while the median worker in high exposure occupations was around the 60th percentile.

Exhibit 11: High exposure occupations have on average higher incomes...



Note: Salary data as of 2024. Source: IPUMS, BLS, Morgan Stanley Research

Exhibit 12: .. with a clear relationship between exposure rate and annual salary



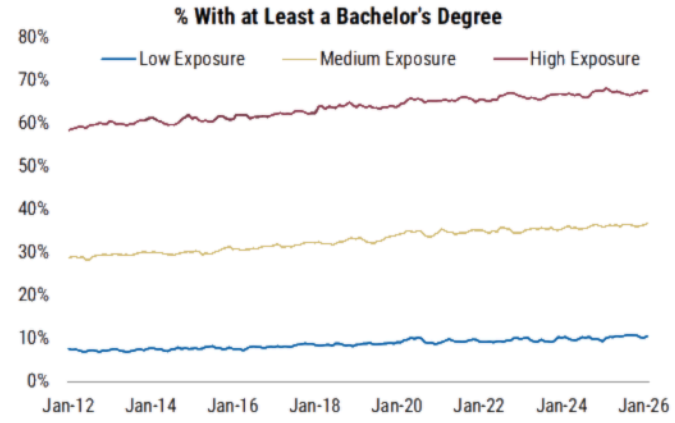
Note: Salary data as of 2024. Source: IPUMS, BLS, Morgan Stanley Research

Similar trends are apparent in education levels. Those in high exposure occupations are more likely to have a college degree, and more likely to have a graduate degree. While only around 10% of individuals in the low exposure group had at least a bachelor's degree, almost 70% of individuals within the high exposure group did (Exhibit 13).

Among workers with only Bachelor's degrees, 40% are in the high exposure group, and among those with graduate degrees, 51% are in this group. These are relatively large

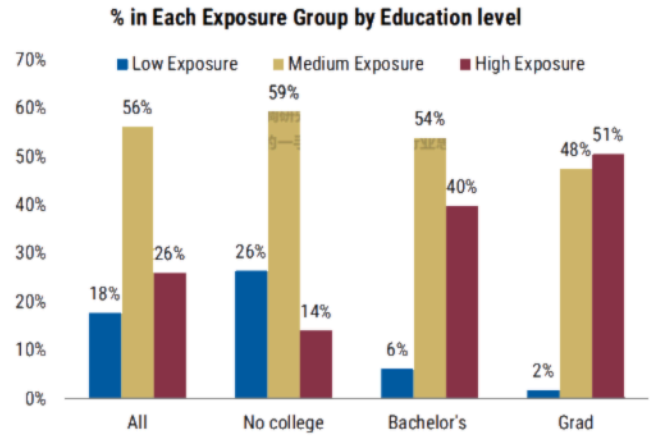
shares considering only 26% of all workers are high exposure by this measure. For those without a college degree, only 14% are high exposure (Exhibit 14).

Exhibit 13: High exposure occupations have a larger share of college-educated workers



Source: IPUMS, BLS, Morgan Stanley Research

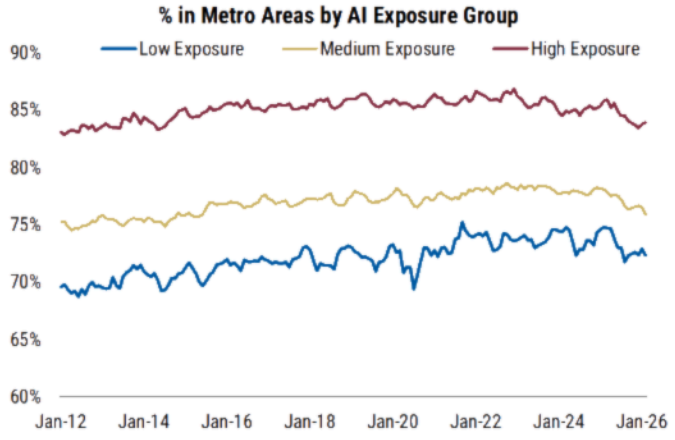
Exhibit 14: 40-50% of workers with Bachelor's degrees or higher fall into the high exposure group



Note: Data as of Feb 2025. Source: IPUMS, BLS, Morgan Stanley Research

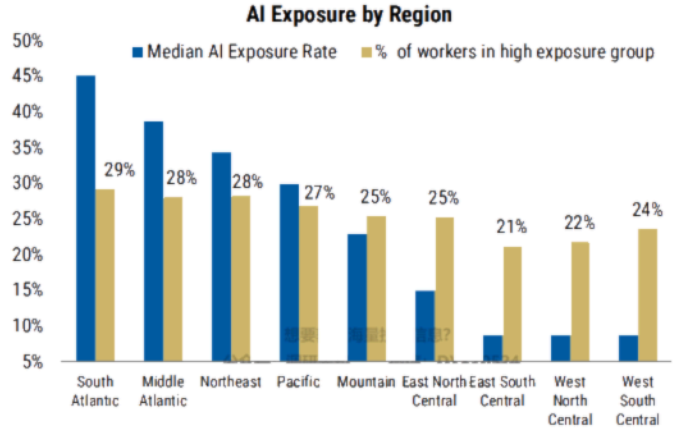
By geography, those in high exposure occupations are more likely to live in metro areas. Around 85% of high exposure workers live in a metro area compared to just over 70% of the low exposure group (Exhibit 15). The east and west coasts also tend to have occupations with higher exposure rates, namely the South Atlantic, Middle Atlantic, Northeast, and Pacific regions (Exhibit 16). In these regions, almost 30% of workers were in the high exposure group compared to around 20% of workers in central regions.

Exhibit 15: A larger share of those in high exposure occupations live in metro areas ...



Source: IPUMS, BLS, Morgan Stanley Research

Exhibit 16: ... and coastal regions have higher exposure rates



Note: Data as of Feb 2025. Source: IPUMS, BLS, Morgan Stanley Research

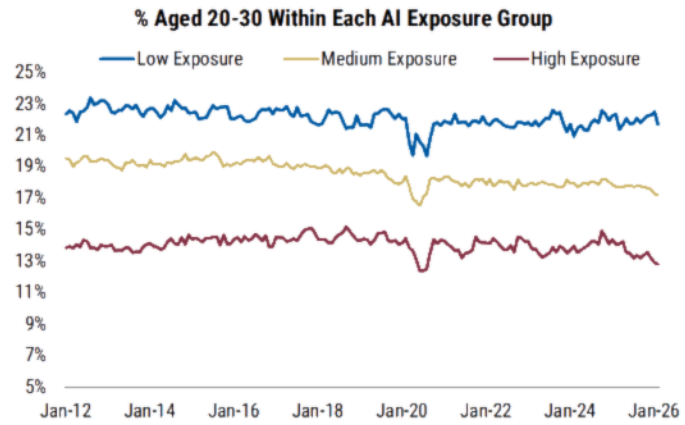
So far, it is clear that high-income, highly-educated, city-dwelling households, or CHIC households, are more occupationally exposed to AI. The final characteristic we look at is age.

High exposure occupations on average tend to be older. For the high exposure group, just 13% of workers are 20-30 years old compared to 22% in the low exposure group (Exhibit 18). Similarly, when we look at exposures within each age group, only 14% of 20-24 year

olds and 24% of 25-29 year olds were in the high exposure group, compared to almost 30% of older age cohorts. These differences could be because more low exposure occupations are related to manual labor, and more high exposure occupations require advanced degrees or prior experience.

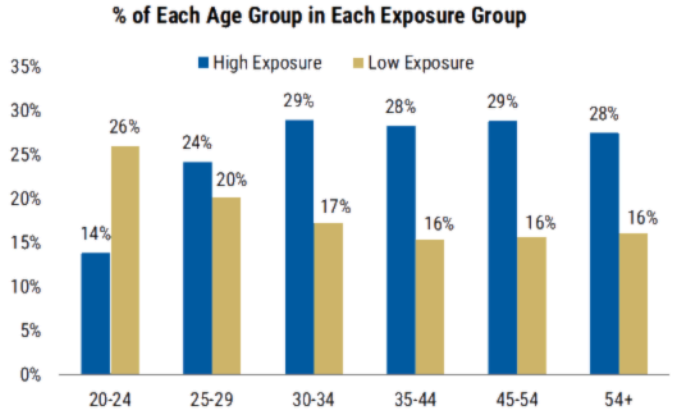
That said, we think the age channel is more nuanced. This definition of exposure does not consider differences in tasks between two workers in the same occupation. Within a given occupation, tasks may differ more by career stage than by other differences such as region. This is where the "automation" vs "augmentation" factor could be important; even if a smaller share of young workers are in highly-exposed occupations, it may be true that within any given occupation, younger workers perform tasks more easily automatable by AI.

Exhibit 17: High AI exposure have a lower share of 20-30yr old workers ...



Source: IPUMS, BLS, Morgan Stanley Research

Exhibit 18: ... And a smaller share of young workers are in high exposure occupations as opposed to older workers



Source: IPUMS, BLS, Morgan Stanley Research

Occupational Exposure: Positive in our base case, with risks in scenarios of rapid diffusion

Whether high occupational exposure to AI is a net positive or net negative is not a foregone conclusion, as we see three potential channels through which AI could affect labor markets: 1) labor displacement could lead to income loss, 2) faster wage growth from productivity gains could raise earnings, and 3) new job creation could create new income opportunities.

Displacement

The first potential transmission channel of AI labor effects to consumers is through displacement. In our recent AI labor market tracker, we found evidence that unemployment is rising more in highly AI-exposed occupations. In th
group, defined the same as we did above, unemployment is about 0
cyclical trends say it should be. While some of this could be due to r
think there is some evidence that AI is contributing to more layoffs
these occupations.

Given our analysis above of which consumers are in these occupatio
rises faster than these workers can be reabsorbed, CHIC households



Within this CHIC group though, we find further distinction. So far, there has been more evidence that younger consumers within these occupations have seen larger displacement effects. We think this makes sense given entry-level tasks are likely more exposed to automation from AI, rather than augmentation. As a result, we would specifically expect young CHIC households to be most exposed to potential labor displacement.

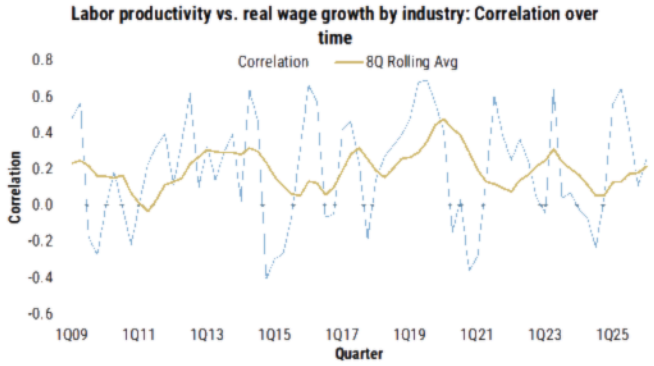
Productivity-Driven Wage Growth

As described previously, in our base case AI leads to faster wage growth, driven by productivity gains. This is in line with historical data, as over the past 20 years, in any given quarter, industries with larger productivity gains also tended to have larger real wage gains (Exhibit 19).

We recently found that industries more exposed to AI have experienced faster productivity growth over the past year. We expect this to continue, and if so, workers in these industries will likely benefit more from the productivity-wage growth channel. So far, there is some evidence here, but it is not definitive; industries more exposed to AI have relatively strong absolute wage growth, but some less exposed industries have experienced larger recent *accelerations* (Exhibit 20).

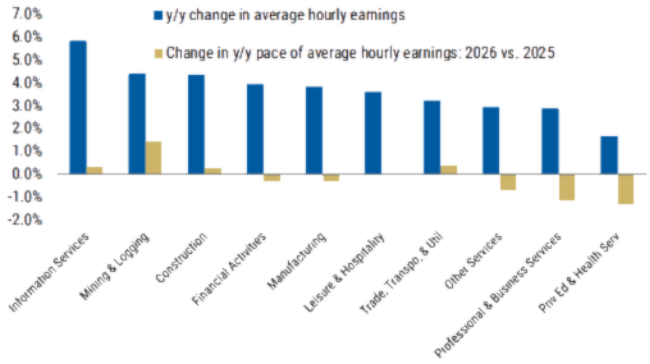
If wage gains accrue to those in high exposure occupations, CHIC households would benefit more (assuming these workers remain in highly exposed occupations throughout any reshuffling that occurs). The wage gains would likely accrue to those for which AI augments rather than automates their tasks, potentially leading to more gains for experienced workers within this group.

Exhibit 19: Over the past 20 years, industries with larger productivity gains have also had larger real wage gains



Source: BEA, BLS, Haver Analytics, Morgan Stanley Research

Exhibit 20: Some more exposed industries have had relatively strong wage growth recently, but accelerations in wage growth are less clear



Source: BLS, Haver Analytics, Morgan Stanley Research

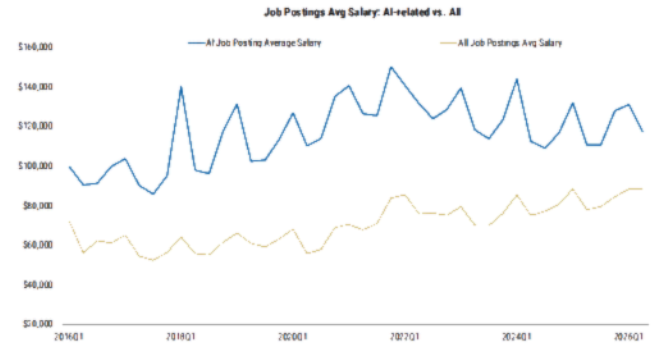
New Job Creation

Finally we consider new job creation. A key question is not only how fast these jobs will be created, but also what these new occupations will be. While it is still early, we can use initial data on AI-related job postings to try to glean which consumers will be most suited for these new occupations. Our Alphawise team tracks AI job postings using LinkUp data and filtering for AI-related key words.

We do not have the salary for each job posting, given that salary postings are not required in every state. However, by looking at detailed industry groups of each posting, we can

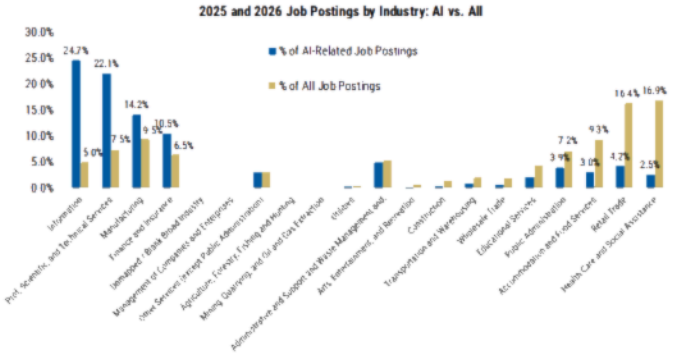
estimate a salary for the job. When we do so, we see that the average salaries for AI-related postings are consistently higher than for non-AI postings (Exhibit 21). AI-related job postings are also concentrated more so in industries that we would expect to be more AI-exposed such as professional and technical services and information, and much less concentrated in less exposed industries such as health care and retail trade (Exhibit 22).

Exhibit 21: AI-related job postings tend to be in industries that are higher-income skewed



Source AlphaWise, LinkUp, Morgan Stanley Research

Exhibit 22: Industries more exposed to AI such as professional services, information services, and finance, account for a larger share of AI job postings

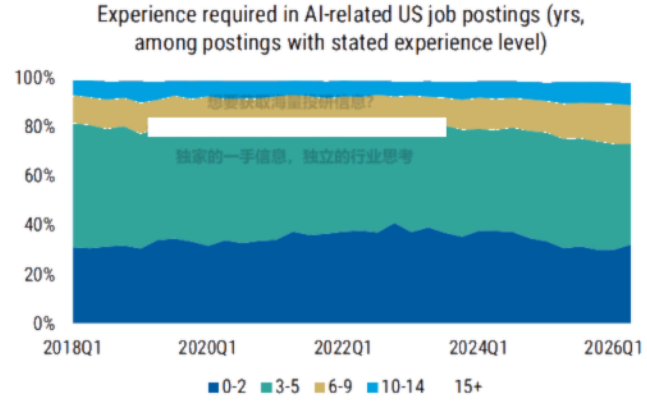


Source AlphaWise, LinkUp, Morgan Stanley Research

In terms of experience level, AI-related job postings are more likely to state a numerical experience requirement. Among all postings, over 60% had no clear experience requirement, driven by food service and retail postings which often did not state a numerical preference. Among AI postings, only 35% had no clear preference.

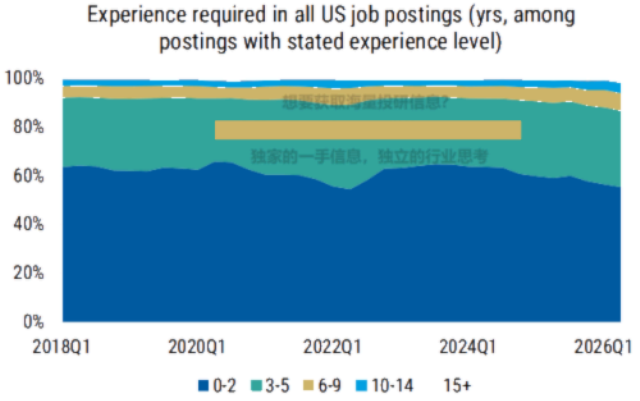
When we limit both universes to only postings with numerical experience preferences, we see that AI-related postings tilt away from entry-level roles. In the most recent data, 55% of all postings were targeted at workers with 0-2 years of experience (Exhibit 24). For AI-related postings, only 32% were targeted at this group (Exhibit 23). AI-related postings instead tilted more heavily to those with 3-14 years of experience.

Exhibit 23: AI-related job postings tilt towards some level of experience



Source LinkUp, AlphaWise, Morgan Stanley Research

Exhibit 24: While all postings are skewed more towards entry level roles



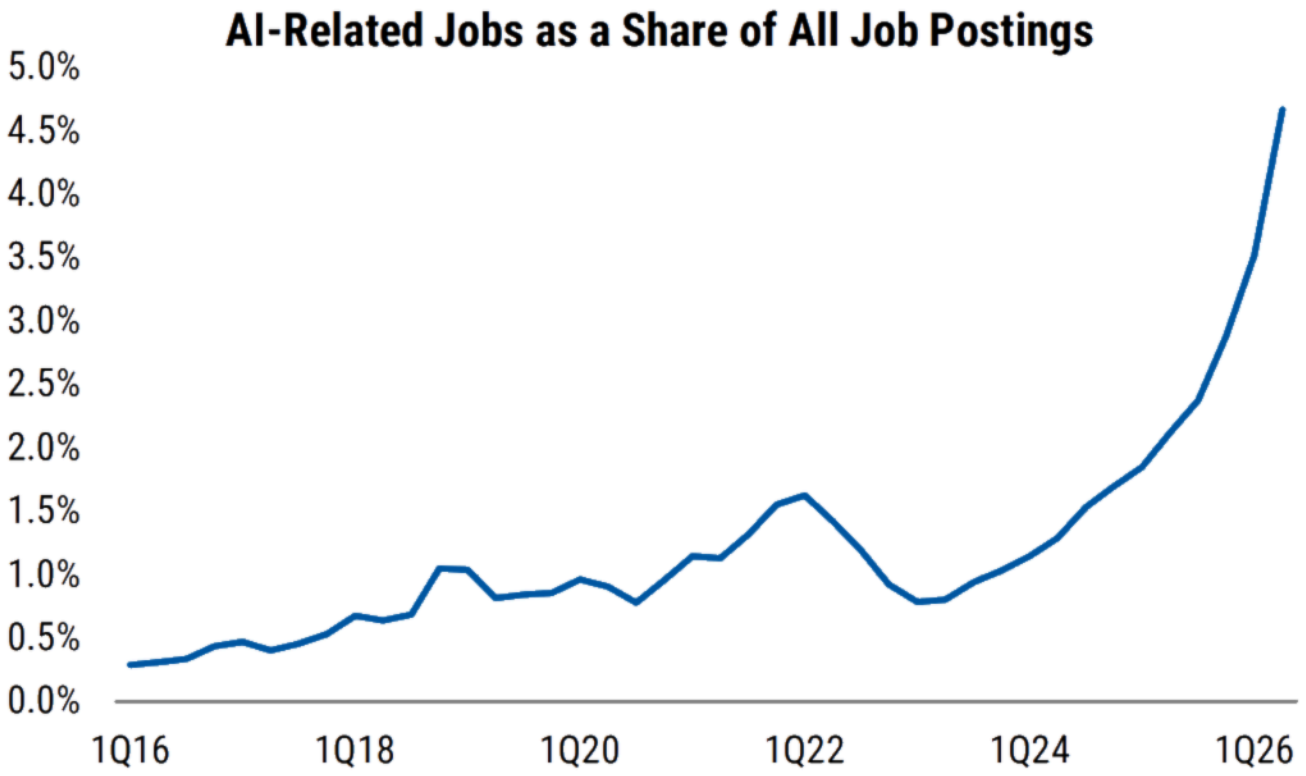
Source LinkUp, AlphaWise, Morgan Stanley Research

The types of tasks and jobs created by AI can change over time as AI use becomes more widespread. For now, however, the same CHIC households that are more exposed to AI in

their current occupations, and specifically those with some experience, also appear better positioned for the new jobs AI is creating.

Over the past year, AI-related jobs have risen from just 2.1% of all job postings to 4.7% (Exhibit 25). In our base case, faster wage growth and new task creation outweigh the initial labor displacement, so demand and income for more exposed workers rise. That said, this will very much be dependent on the relative speeds of AI-diffusion and task creation.

Exhibit 25: AI-related jobs have been increasing as a share of job postings



Source: AlphaWise, LinkUp, Morgan Stanley Research

What About Embodied AI/Robotics?

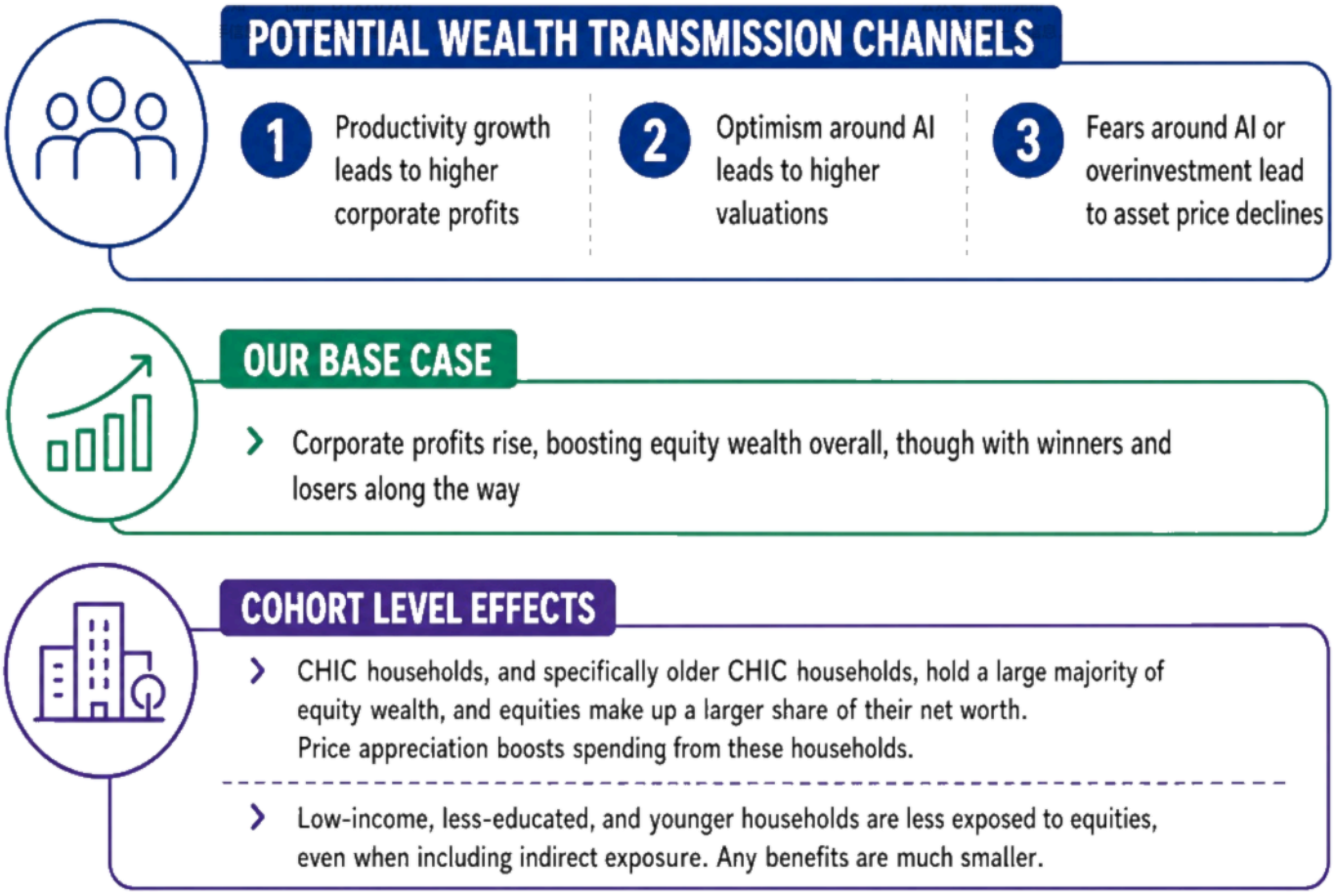
William Tackett

The exposure analysis above covers agentic and software AI, which operates in the digital, non-physical world and skews toward higher-income, college-educated, urban coastal workers. Embodied AI, meaning robotics and physical automation, hits close to the mirror image of that group: the manual-labor occupations least exposed to agentic AI. These workers handle physical tasks like manipulation, movement, and operation in messy environments, exactly what robotics targets. Timing is an important caveat. Software AI tends to diffuse faster, as scaling an additional instance is generally cheaper than deploying physical hardware. We

expect robotics to move slower, weighed down by hardware costs, safety requirements, heavy capital intensity, and a shortage of the real-world physical interaction data that robotics models need to train on. Our Global Robot Model projects just 35 million total robots in the US by 2030, up from 15 million in 2026, a notable increase but not enough to seriously dent the labor force, and these may well add to productivity rather than replace workers one for one. Humanoid-specific robots do not reach 1 million in the US until 2035. That longer runway gives the manual-labor cohort time to adjust, and as with agentic AI, exposure can mean augmentation, think cobots and exoskeletons, not just automation.

Wealth: AI-exposed households in the labor market benefit most from higher returns to capital

Exhibit 26: Potential Wealth Transmission Channels of AI



Source: Morgan Stanley Research

AI-Related Wealth Exposures by Cohort

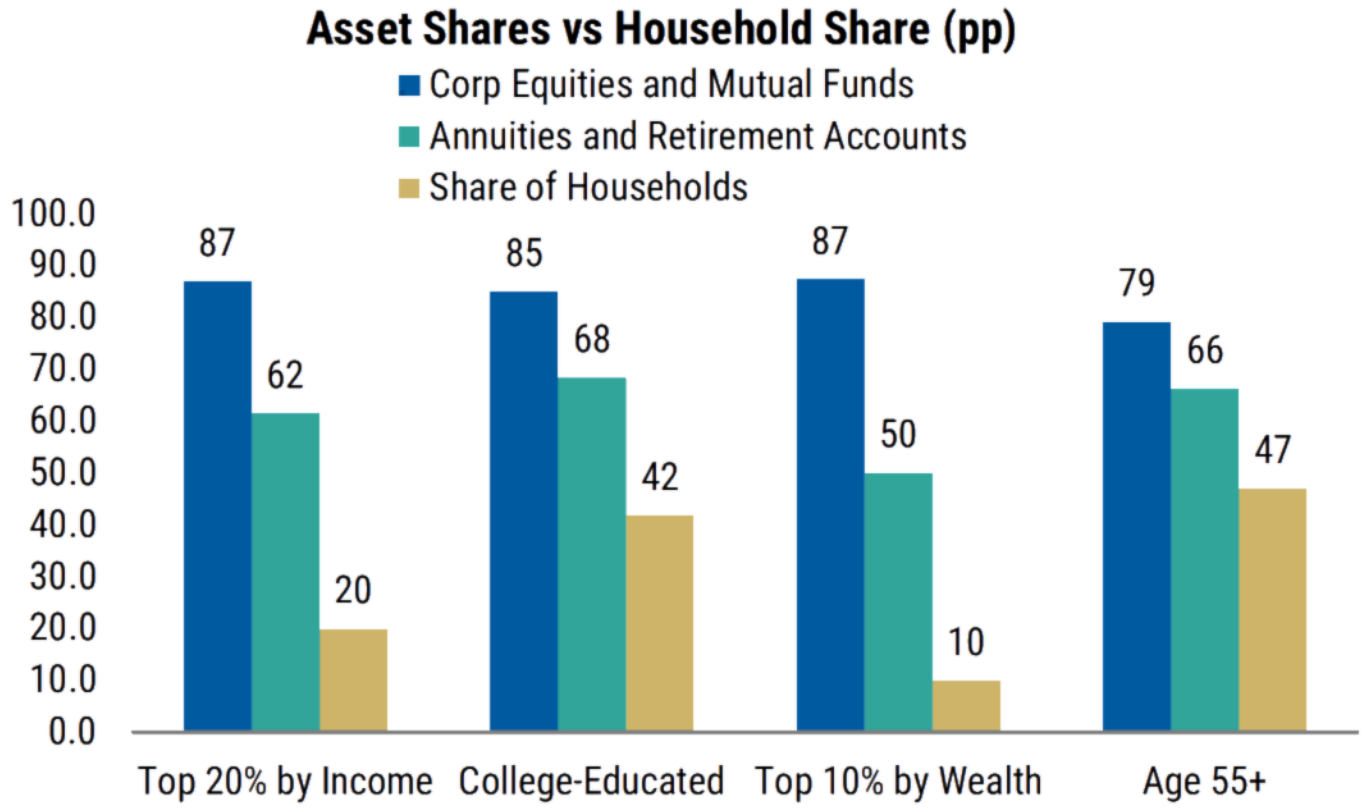
The second channel through which AI could affect consumers is wealth effects, under the assumption that the AI innovation cycle boosts returns to capital in the same way as the internet and digital revolution did.

The top 20% income cohort accounts for 87% of direct consumer holdings of corporate equities and mutual funds. By education and age, the results are similar; college-educated households make up only 42% of all households but account for 85% of these holdings, and those 55 and older households make up only 47% of households but account for 79% of holdings (Exhibit 27).

Equity exposure can also come indirectly through retirement accounts. Retirement holdings and annuities are still much more concentrated among these same cohorts of

consumers, even if slightly less so than direct holdings. The top 20% income cohort accounts for over 60% of retirement and annuity holdings, while college-educated households account for almost 70% and those over 55 account for 66%.

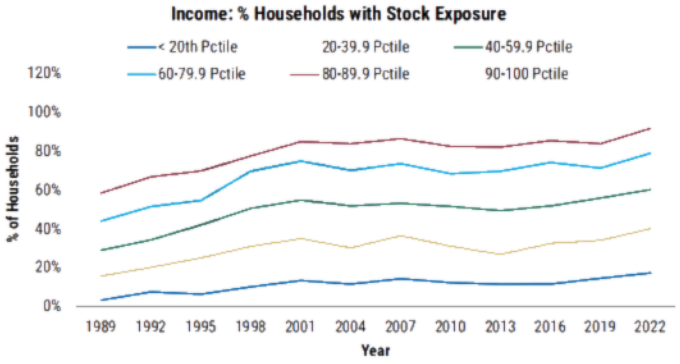
Exhibit 27: Both direct equity holdings and retirement accounts are much more concentrated among high-income, high-wealth, college-educated, and older households



Note: Data as of 4Q25. Source: Federal Reserve Board, Haver Analytics, Morgan Stanley Research

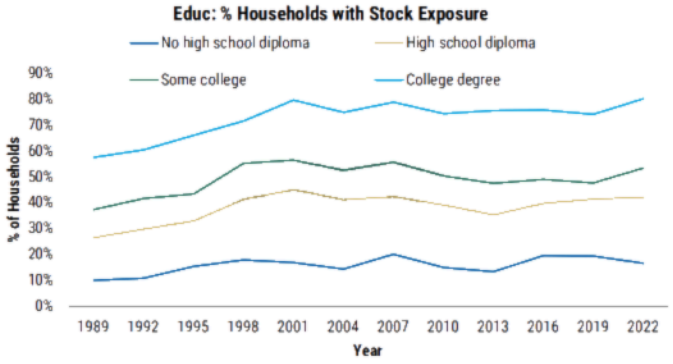
CHIC households not only hold more equities in dollar terms, but also they are much more likely to own equities at all. While the share of consumers in the US with equity exposure has grown over time, divergences across cohorts are still significant. For the bottom income quintile, as of the most recent data under 20% of households had exposure to equities, compared to over 80% of households in the top quintile (Exhibit 28). The differences for non-college-educated households versus college-educated households are similar (Exhibit 29).

Exhibit 28: A much larger share of upper-income households have any exposure to equities ...



Source: Federal Reserve Board, Haver Analytics, Morgan Stanley Research

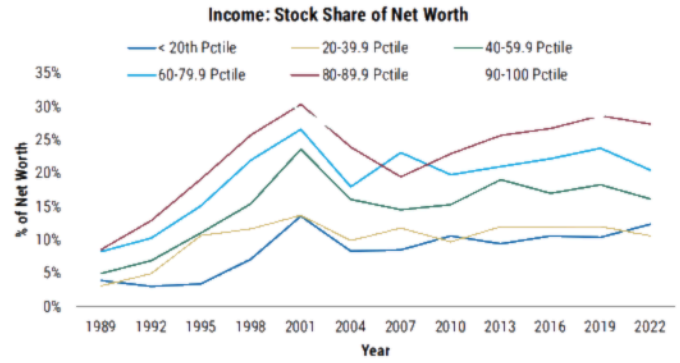
Exhibit 29: ... and the same is true for college-educated households



Source: Federal Reserve Board, Haver Analytics, Morgan Stanley Research

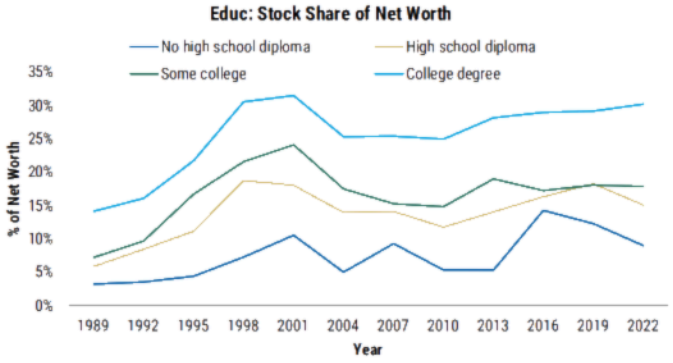
With a greater share of households exposed, equities make up a larger share of net worth for CHIC households as opposed to lower-income and less-educated cohorts. For the top 20% income cohort, stocks (held both directly and indirectly) make up around 30% of their net worth, while for the bottom 40% income cohort stocks make up only 10% (Exhibit 30). Similarly, stocks make up around 30% of net worth for college-educated households versus only 10-15% of net worth for non-college-educated households (Exhibit 31). As a result, movements in equities have more ability to drive changes in wealth, and thus changes in consumption, for CHIC households.

Exhibit 30: Stocks make up a much larger share of net worth for upper-income households ...



Source: Federal Reserve Board, Haver Analytics, Morgan Stanley Research

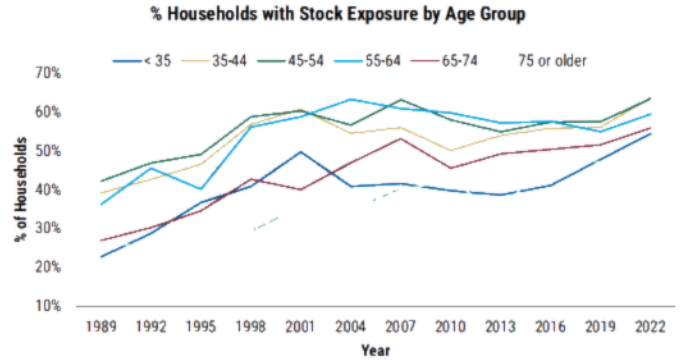
Exhibit 31: ... and for more educated households



Source: Federal Reserve Board, Haver Analytics, Morgan Stanley Research

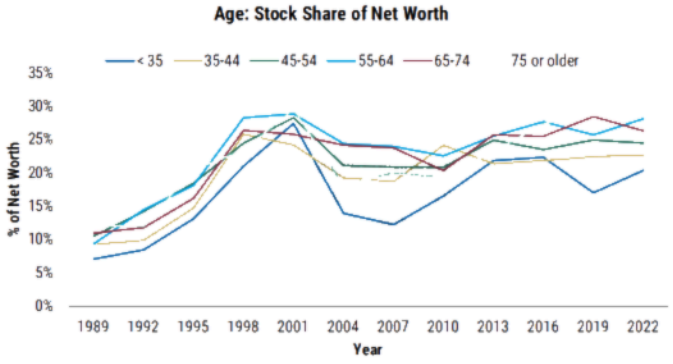
The percent of households exposed to equities is more similar across age cohorts but is the highest for the middle age groups. Over 60% of households aged 35-64 had equity exposure as of the most recent data, compared to 50-55% of the younger and older groups (Exhibit 30). However, given differences in dollar amounts, stocks still make up a larger share of overall wealth for older households. Stocks make up around 20% of net worth for households under 35 compared to closer to 30% for households 55+ (Exhibit 31). This is not as stark of a difference as when separating by income or education level, but we also do not have granular data at the very young end of the spectrum (below 30 or below 25).

Exhibit 32: For middle age groups, the percent of households with any equity exposure is largest



Source: Federal Reserve Board, Haver Analytics, Morgan Stanley Research

Exhibit 33: Equities make up larger share of net worth for older households, but the differences are not as stark



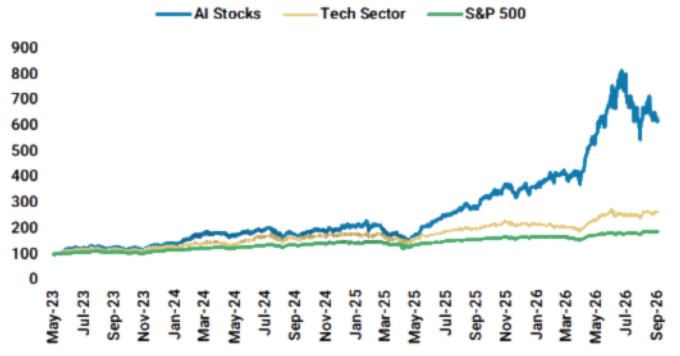
Source: Federal Reserve Board, Haver Analytics, Morgan Stanley Research

Wealth Effects: Positive in our Base Case and in Data So Far

In our base case, equity exposure is a net positive. Corporate profits rise, leading to increases in equity prices and wealth. Financial wealth effects, or the increase in spending generated by increases in financial wealth, are estimated to be relatively small (around 3-5 cents spent for every dollar increase in wealth). However, large enough moves can still drive meaningful changes. Given higher absolute and relative exposures, we expect CHIC households, and specifically older CHIC households, to benefit disproportionately from this channel.

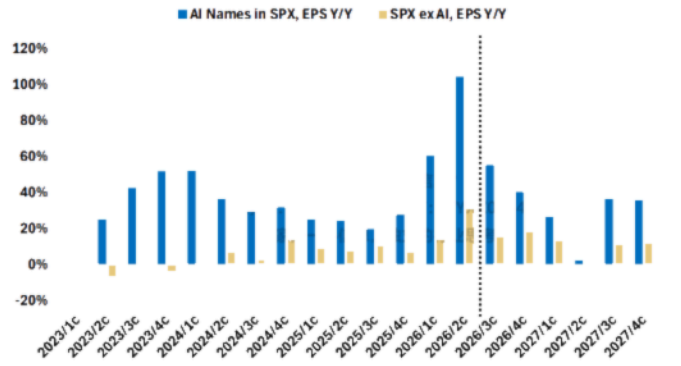
So far, this has already been the case. AI-related stocks have been increasingly driving growth in the S&P 500 (Exhibit 34). According to our equity strategy colleagues, S&P 500 earnings are being skewed upward by unrealized gains in AI investments, and they expect that AI companies (enablers or adopters) will drive close to 40% of EPS this year and next.

Exhibit 34: AI-related stocks are a key market driver



Source: Bloomberg, Morgan Stanley Research

Exhibit 35: EPS growth has been much stronger for AI names

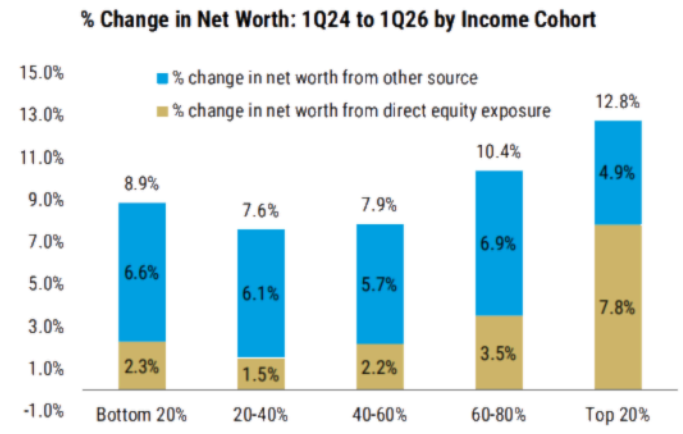


Source: Factset, Morgan Stanley Research

With this AI-related appreciation in stock prices, we have seen significant increases in household wealth just over the past two years. Household wealth rose by around $21tn from 1Q24 to 1Q26, with direct exposure to equities accounting for half of that increase (despite only making up only around 30% of total wealth). High-income and older consumers have had the largest percent increases in net worth over that period, partly

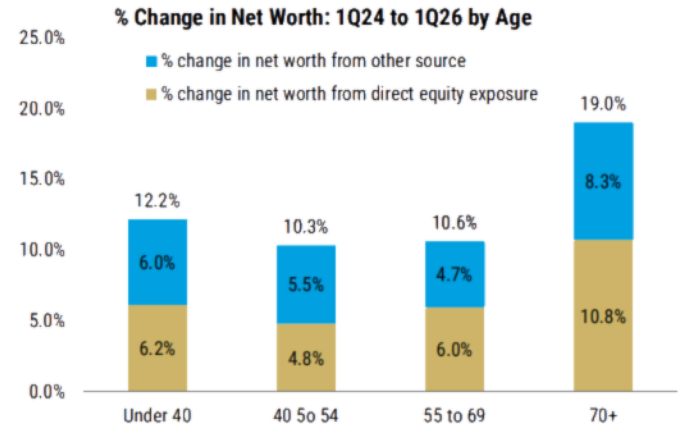
due to their higher equity exposure (Exhibit 36 and Exhibit 37).

Exhibit 36: High-income consumers have had larger recent increases in net worth, driven by equity gains ...



Source: Federal Reserve Board, Haver Analytics, Morgan Stanley Research

Exhibit 37: ... as have older consumers

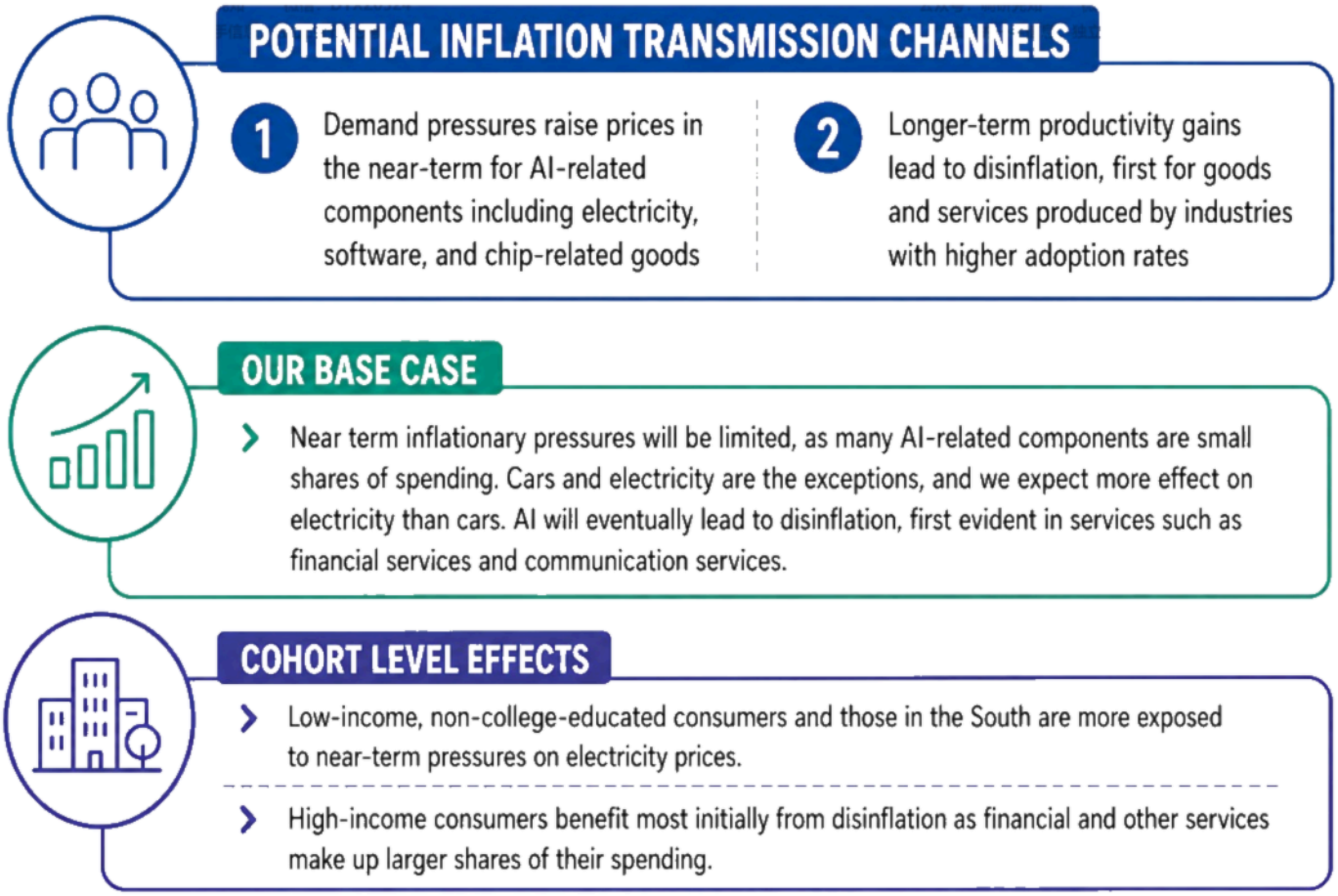


Source: Federal Reserve Board, Haver Analytics, Morgan Stanley Research

Still, we cannot ignore a potential bear case scenario. Innovation waves often come with boom bust cycles, and there could be a period where there is a downturn in financial markets. If so, these same cohorts would be more exposed to the downside. A large and prolonged decline in asset prices (-25-30%+) could be perceived as permanent, prompting these households to pull back on spending. While trickle-down effects would affect other cohorts as well, CHIC households would be most exposed to the initial negative wealth effects.

Inflation: Near-term demand pressures give way to supply-side disinflationary forces

Exhibit 38: Potential Inflation Transmission Channels of AI



Source: Morgan Stanley Research

Income and wealth gains will ultimately matter relative to the changes in prices consumers face. If AI leads to higher inflation, consumers will have less purchasing power. Meanwhile, if AI leads to price declines, the quantity of goods and services consumers can buy will increase.

Near term demand side pressures

Stronger demand for goods and services related to the AI infrastructure build or AI adoption could lead to near-term inflationary pressures. If so, we would expect to see these price increases in electricity, software, and categories of goods exposed to chips (phones, televisions, household appliances, and cars). Many of these categories have relatively small weights in both PCE and CPI prices. As a result, we are still optimistic about disinflation this year and next in our base case. We expect payback from tariff

inflation to more than offset these AI pressures, while other components, such as shelter, continue to soften. The AI pressures are therefore not large enough to change our base case expectation that the Fed will remain on hold this year.

That said, there is upside risk to these inflation forecasts. Software prices, for example, accelerated more than we expected earlier this year, boosting core inflation noticeably even despite its small weight. Upcoming methodology changes will likely put downward pressure on software inflation rates, but there could be similar larger-than-expected acceleration in other categories. We have also already seen more pressures in some AI-related categories within PPI. These higher input costs will likely drive either margin pressure or further consumer price increases, which could be larger than we expect. While there is uncertainty around the magnitude, these near-term price increases could weigh on consumer purchasing power and lead to softer demand.

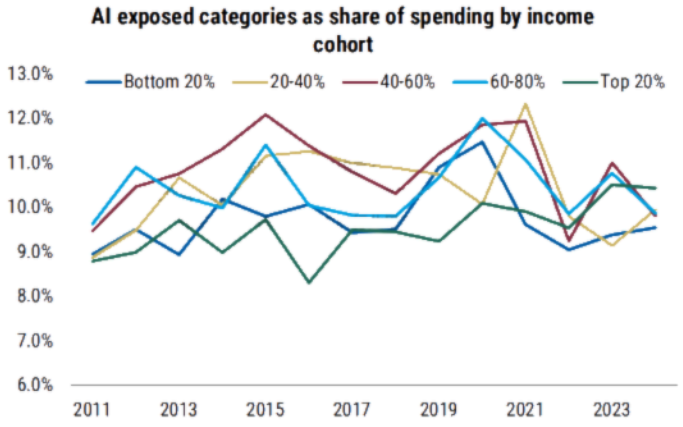
In the below exhibits, we combine electricity, vehicles, computers, telephones, computer software, game consoles, and major appliances to create an "AI-exposure" basket. We then look at what share of spending this basket, and different parts of the basket, makes up for different cohorts. If items with higher inflation rates make up a larger share of spending for a given consumer, then their experienced inflation rate will be higher.

By income group, exposure is relatively even for the basket as a whole, with these AI-related items making up around 10% of spending. However, the composition differs. Telephones, computers, major appliances, software, and game consoles altogether make up right around 1% of spending across cohorts. Spending on vehicles is a larger share for upper-income cohorts (8% for upper versus 5% for lower) while spending on electricity is a larger share for lower-income cohorts (2% for upper versus 4% for lower).

So far, we see more evidence of AI-related pressures on electricity prices than on car prices. For vehicles, higher chip costs have not yet been passed through to consumer prices and have instead been absorbed by OEM margins. We expect this to continue in the near term, though there is more uncertainty about future pass through. For electricity, we see evidence that in areas with higher data center concentration, electricity prices have risen more. While we do not expect a sharp increase in electricity prices because of AI, we do expect electricity prices to remain sticky and above the pre-Covid trend.

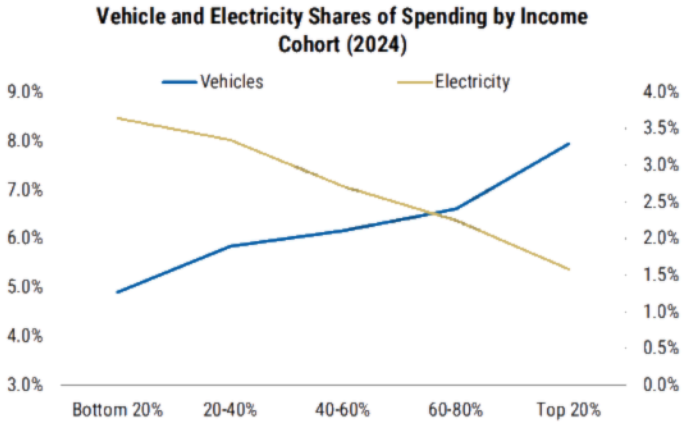
If our assumptions around vehicles and electricity are correct, in the near term, low-income cohorts are likely more exposed to these AI price pressures. High-income consumers also have more ability to trade down in times of temporary price increases, consistent with the data which shows experienced inflation rates of low-income consumers tend to be higher when inflation is above target.

Exhibit 39: Exposures to categories with potential near term AI price pressures are similar across income cohorts...



Note Here "AI exposed categories" include electricity, vehicles, computers, telephones, computer software, video game hardware and accessories and major appliances. Source BLS Haver Analytics, Morgan Stanley Research

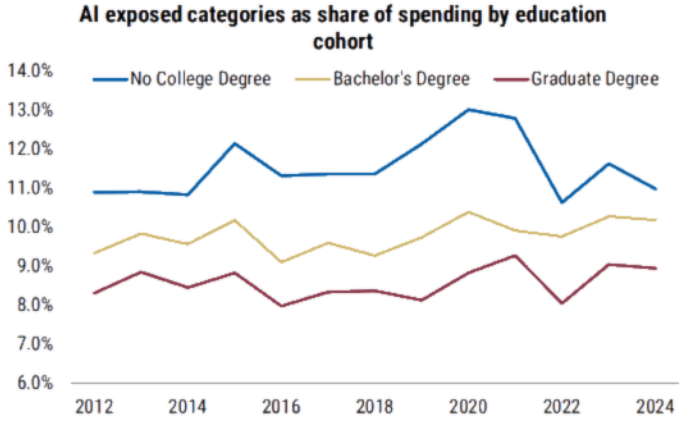
Exhibit 40: ... but high-income consumers are more exposed to vehicles while low-income are more exposed to electricity



Source BLS Haver Analytics, Morgan Stanley Research

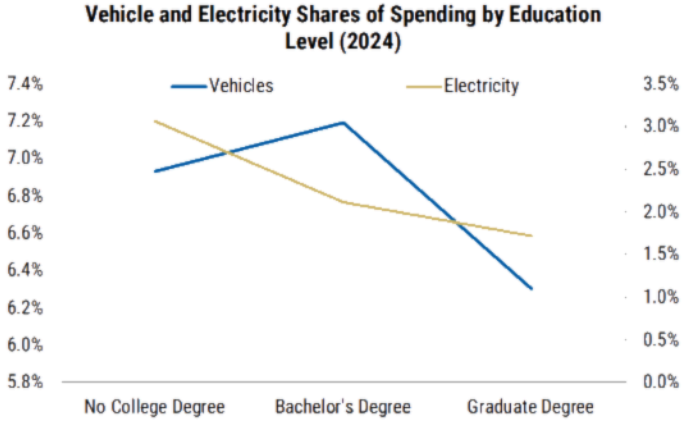
Looking by education level, those with no college degree are clearly more exposed to the "AI-exposed" basket. Again, the exposure across the categories excluding cars and electricity are similar. However, those with no college degree are more exposed to electricity and are similarly exposed to vehicles.

Exhibit 41: Non-college-educated consumers are more exposed to AI price pressures near-term ...



Note Here "AI exposed categories" include electricity, vehicles, computers, telephones, computer software, video game hardware and accessories and major appliances. Source BLS Haver Analytics, Morgan Stanley Research

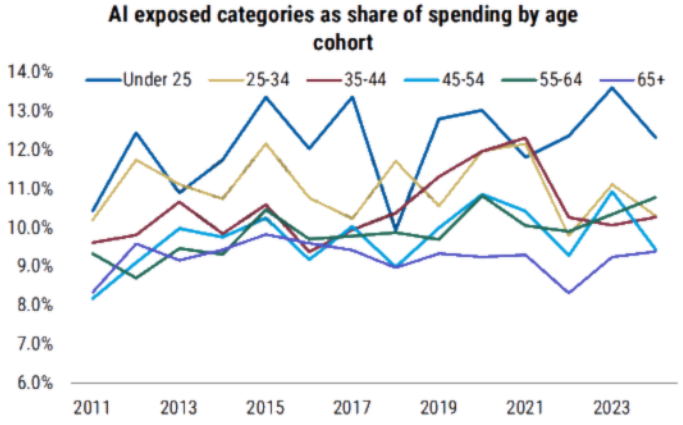
Exhibit 42: ... with more exposure to electricity and similar exposure to vehicles



Source BLS Haver Analytics, Morgan Stanley Research

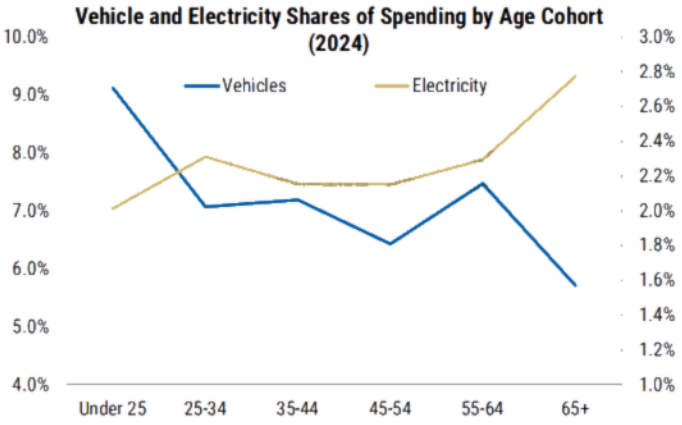
By age, younger consumers are slightly more exposed to this AI basket. These consumers have more exposure to the smaller categories (computers, phones, software, etc) and also to vehicle purchases. Electricity exposure is similar across most age groups, except for those over 65, for whom it is higher, potentially leading to more near-term pressure for this older group as well.

Exhibit 43: Younger consumers are more exposed to AI price pressures near term ...



Note: Here "AI exposed categories" include electricity, vehicles, computers, telephones, computer software, video game hardware and accessories and major appliances. Source: BLS, Haver Analytics, Morgan Stanley Research

Exhibit 44: Vehicle spending is a larger share for young consumers while electricity is a larger share for the oldest cohort



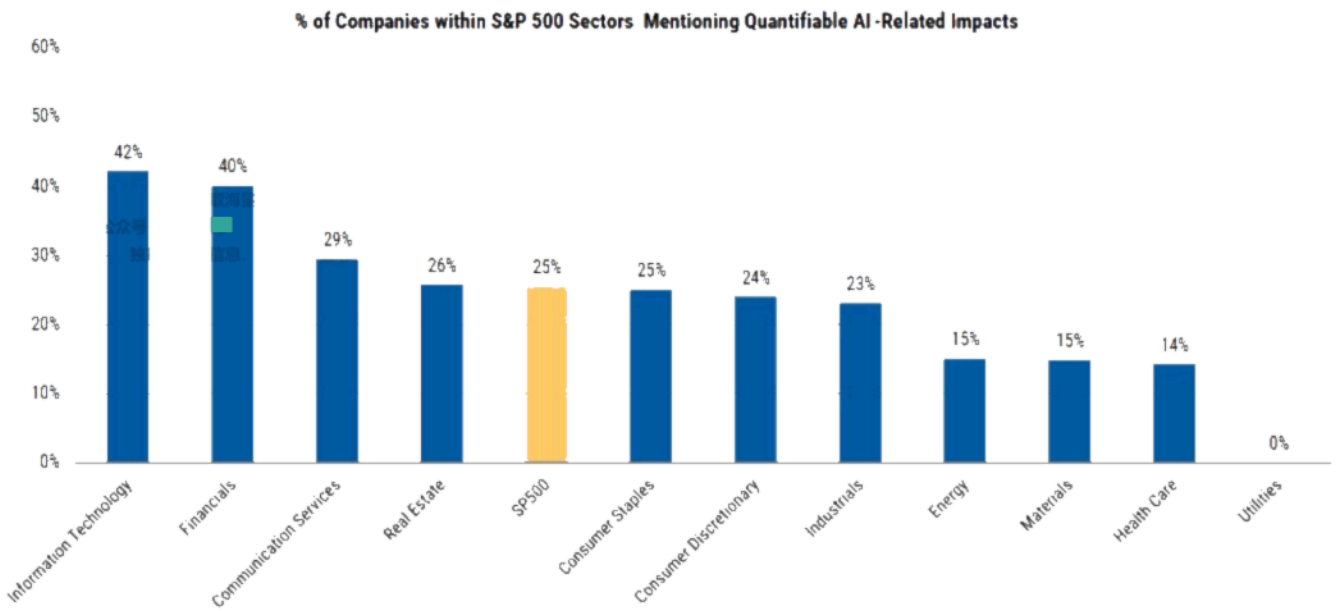
Source: BLS, Haver Analytics, Morgan Stanley Research

Finally, regional differences will play an important role in how consumers experience these near term price pressures. As described in our recent note, regional data provide evidence that data center demand is creating inflationary pressures, as residential electricity prices in the South Atlantic region have accelerated much faster than the national median. We can also see this through spending data, where electricity costs have made up a much larger share of income for consumers in the South. According to the Consumer Expenditure Survey, households in the South have on average lower income and lower rates of college-educated households as compared to the national average.

Longer term disinflation

Whether AI supply-side gains result in less overall inflation will depend on a number of factors, including the cyclical position of the economy, but, at a minimum, AI productivity enhancements should not boost inflation longer term. In our base case, AI productivity gains lead to disinflation, and this is likely led by industries with higher adoption rates. So far, AI adoption rates are highest in the information technology industry and in services industries such as financials and communication services (Exhibit 45).

Exhibit 45: Percent of Companies within S&P 500 Sectors Mentioning Quantifiable AI-Related Impacts



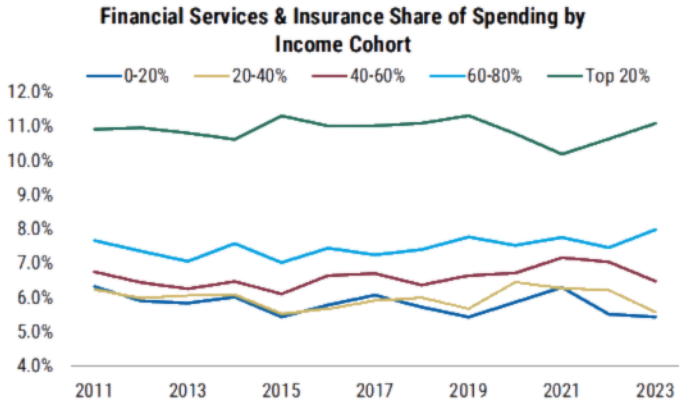
Source: Morgan Stanley Research

If these faster adopters experience earlier productivity gains, we would expect the disinflation first to appear in goods and services produced by these industries. As we saw above, exposure to goods produced by technology firms, such as computers, smartphones, and software, is relatively similar across income cohorts. We now focus on exposures to services provided by these industries. For this part, the data available only allow us to separate by income cohort, but we can infer results about the other demographic groups.

Financial services and insurance make up around 11% of spending for the top 20% income cohort compared to just 4% for the bottom 20% cohort. Similarly, "other services", which include professional and communication services, make up 11% of spending for the highest-income quintile and just 5% for the lowest.

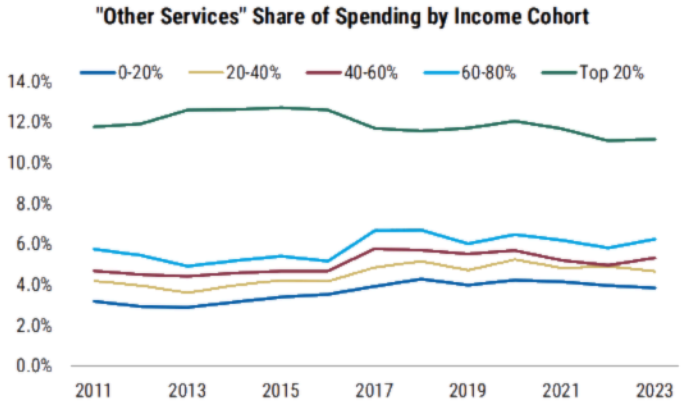
If disinflation first occurs in these categories of spending, high-income cohorts could experience lower inflation rates relative to the aggregate. Given wealth levels and other similar characteristics, we expect this higher exposure is likely true for college-educated, city-dwelling, and older consumers as well.

Exhibit 46: High-income cohorts have more exposure to financial services and insurance ...



Source: BLS, BEA, Morgan Stanley Research

Exhibit 47: ... as well as to "other services" including professional and communication services



Source: BLS, BEA, Morgan Stanley Research

Bringing it All Together

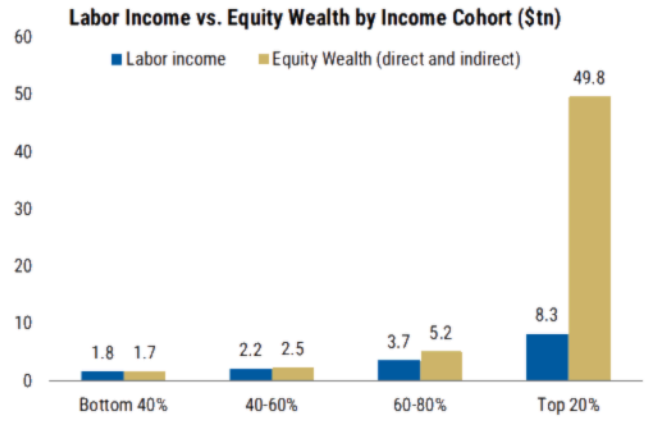
Overall, CHIC households are more exposed to labor displacement, but also more exposed to productivity-driven wage growth, new job creation, wealth effects, and longer-term disinflation. Lower-income, less-educated households are less exposed to displacement but also less exposed to the upside channels and more exposed to near-term inflationary pressures. We now assess how these opposing forces balance for each cohort in our base and bear case AI scenarios.

Base Case: Task creation and wealth effects offset labor displacement, and CHIC households benefit most

As described previously, in our base case for AI, we expect a temporary increase in unemployment (+0.2-0.5pp at the peak), but this is more than offset by an acceleration in wage growth, employment gains from new occupations and tasks, disinflation, and positive wealth effects. Past innovation waves point to a similar outcome, but this is still a relatively optimistic scenario in which output and income ultimately increase. Below, we use data on income and wealth levels to quantify this mechanism and assess how different cohorts will fare.

Overall, we consider labor income the main driver of consumer spending, as the marginal propensity to consume (MPC) out of labor income is relatively high. That said, large enough changes in wealth can also drive meaningful changes in spending. For different income groups, the importance of these two drivers will vary.

Exhibit 48: For high-income households, equity wealth is very elevated relative to labor income



Source: BLS, Federal Reserve Board, Haver Analytics, Morgan Stanley Research

For lower-income households, equity wealth is small enough that labor income remains the dominant driver of spending. For the top income cohort though, equity wealth is roughly six times annual labor income. (Exhibit 48). Even with a much lower MPC out of wealth, relatively modest asset-price gains can offset the spending effects of labor-income losses.

These differences are demonstrated in Exhibit 49, Exhibit 50, and Exhibit 51 below. Each exhibit shows the percent increase in permanent equity wealth needed to offset the spending effects of a 1% decline in labor income. We show this for the bottom 40% income cohort, top 20%, and 80-90th percentile. [2] Each exhibit includes different assumptions of marginal propensities to consume (MPCs) out of income and wealth, and we highlight the range we find most likely for each group.

If we assume a 90% MPC out of labor income and 4% MPC out of financial wealth for all cohorts, the bottom 40% cohort would need their equity wealth to increase by 24% to offset a 1% decline in labor income. The top 20% cohort would need

2. Note that in these estimates, the increase in equity wealth is assumed to be "permanent." In other words, these consumers need to believe that their resources have permanently risen in order for the increase in wealth to drive spending. For this to happen, the increase would likely need to be sustained.

an increase of only 4% in their equity wealth, and the 80-90th percentile cohort (excluding the very top as they may drive large differences) would still need an increase of only 8%.

In practice, the gap may be even larger because upper-income households likely have lower MPCs out of labor income. Differences in wealth effects are less clear: some papers have found lower MPCs out of wealth among high-income households, but lower-income households' equity holdings are more concentrated in illiquid retirement accounts, potentially implying the opposite. If we assume the same wealth effects for each group and a lower MPC out of labor income for high-income consumers, the increase in equity wealth needed to offset a decline in labor income for the high-income cohort is even lower.

Exhibit 49: Bottom 40% Income Cohort: Percentage increase in permanent equity wealth needed to offset spending effects of a 1% decline in labor income

		Marginal propensity to consume out of labor income							
		50%	60%	70%	80%	85%	90%	95%	100%
Marginal propensity to consume out of financial wealth	1%	53%	63%	74%	84%	90%	95%	100%	106%
	2%	26%	32%	37%	42%	45%	48%	50%	53%
	3%	18%	21%	25%	28%	30%	32%	33%	35%
	4%	13%	16%	18%	21%	22%	24%	25%	26%
	5%	11%	13%	15%	17%	18%	19%	20%	21%
	6%	9%	11%	12%	14%	15%	16%	17%	18%
	7%	8%	9%	11%	12%	13%	14%	14%	15%
	8%	7%	8%	9%	11%	11%	12%	13%	13%

Source: BEA, Federal Reserve Board, Morgan Stanley Research

Exhibit 50: Top 20% Income Cohort: Percentage increase in permanent equity wealth needed to offset spending effects of a 1% decline in labor income

		Marginal propensity to consume out of labor income							
		50%	60%	70%	80%	85%	90%	95%	100%
Marginal propensity to consume out of financial wealth	1%	8%	10%	12%	13%	14%	15%	16%	17%
	2%	4%	5%	6%	7%	7%	7%	8%	8%
	3%	3%	3%	4%	4%	5%	5%	5%	6%
	4%	2%	2%	3%	3%	4%	4%	4%	4%
	5%	2%	2%	2%	3%	3%	3%	3%	3%
	6%	1%	2%	2%	2%	2%	2%	3%	3%
	7%	1%	1%	2%	2%	2%	2%	2%	2%
	8%	1%	1%	1%	2%	2%	2%	2%	2%

Source: BEA, Federal Reserve Board, Morgan Stanley Research

Exhibit 51: 80-90th Percentile Income Cohort: Percentage increase in permanent equity wealth needed to offset spending effects of a 1% decline in labor income

		Marginal propensity to consume out of labor income							
		50%	60%	70%	80%	85%	90%	95%	100%
Marginal propensity to consume out of financial wealth	1%	19%	23%	26%	30%	32%	34%	36%	38%
	2%	9%	11%	13%	15%	16%	17%	18%	19%
	3%	6%	8%	9%	10%	11%	11%	12%	13%
	4%	5%	6%	7%	8%	8%	8%	9%	9%
	5%	4%	5%	5%	6%	6%	7%	7%	8%
	6%	3%	4%	4%	5%	5%	6%	6%	6%
	7%	3%	3%	4%	4%	5%	5%	5%	5%
	8%	2%	3%	3%	4%	4%	4%	4%	5%

Source: BEA, Federal Reserve Board, Morgan Stanley Research

Of course, much larger increases in unemployment could lead to nonlinear effects, and aggregate spending outcomes do not capture potential welfare effects at the individual level. At the aggregate level, these data confirm the finding from our general equilibrium model; in terms of spending and overall economic outcomes, feedback effects from AI (including asset market moves) are just as important as initial productivity and displacement effects. While it might be intuitive that AI could lead to white-collar job loss and thus weaker high-income spending, these data point to the importance of considering all transmission channels in the outlook for this cohort.

In the base case outcome described above, CHIC households benefit most. These consumers ultimately experience the largest increase in resources due to their higher exposures to equity prices, productivity gains, new tasks, and disinflation. Within this group, some consumers (potentially younger households, who are more exposed to displacement and less exposed to asset markets) might be worse-off in the short-term, but others will be better off. Overall, spending for this cohort rises most and income and wealth inequality widen, as was the case in prior innovation waves.

Given these CHIC households account for a large portion of consumer spending, positive outcomes for this group as a whole mean that the overall drag on spending from displacement should be more modest. CHIC households also drive even larger shares of discretionary spending categories, including big-ticket items like furniture and vehicles, luxury goods, and recreational services such as entertainment. Our positive outlook for the high-end consumer means spending in these discretionary spending categories should remain robust.

Exhibit 52: Consumer Expenditure Survey Spending Shares by Cohort

	All Spending	Groceries	Restuarants	Alcohol	Shelter	Utilities	Furniture	Apparel	Vehicles	Gas	Public Transit (inc airfare)	Health Care	Entertainment	Personal Care	Education	Tobacco	Insurance/ Pension
Income Cohort																	
Bottom 20%	9%	12%	8%	8%	11%	12%	9%	11%	6%	10%	8%	11%	7%	9%	11%	19%	1%
20-40%	13%	16%	12%	11%	15%	17%	12%	13%	11%	15%	8%	16%	12%	13%	5%	20%	6%
40-60%	17%	19%	16%	16%	19%	19%	16%	16%	15%	20%	15%	18%	15%	17%	9%	25%	13%
60-80%	23%	23%	24%	23%	22%	23%	25%	20%	22%	25%	22%	23%	23%	23%	17%	20%	24%
Top 20%	38%	30%	39%	44%	34%	28%	39%	39%	45%	30%	46%	32%	43%	37%	58%	15%	56%
Age Cohort																	
Under 25	3%	3%	4%	3%	4%	2%	3%	4%	4%	3%	3%	1%	3%	3%	8%	3%	2%
25-34	14%	14%	15%	14%	16%	13%	13%	17%	15%	15%	12%	9%	13%	13%	14%	13%	16%
35-44	21%	21%	23%	20%	21%	19%	20%	24%	22%	21%	19%	17%	20%	22%	16%	20%	25%
45-54	21%	20%	21%	21%	19%	20%	18%	21%	20%	23%	21%	18%	22%	20%	33%	21%	25%
55-64	19%	17%	18%	18%	18%	19%	21%	18%	21%	18%	20%	19%	18%	18%	21%	22%	22%
65+	22%	24%	19%	23%	23%	27%	25%	17%	19%	19%	26%	36%	24%	23%	8%	21%	10%
Geography																	
Urban	93%	93%	94%	95%	96%	92%	94%	95%	90%	91%	96%	92%	93%	96%	97%	80%	94%
Rural	6%	7%	6%	5%	4%	8%	6%	5%	10%	9%	4%	8%	7%	5%	3%	14%	6%
Education Level																	
No Degree	37%	44%	35%	29%	38%	47%	38%	36%	38%	48%	23%	40%	32%	36%	17%	72%	28%
Bachelor	31%	28%	31%	32%	31%	29%	29%	30%	33%	29%	30%	31%	32%	32%	33%	19%	34%
Grad	32%	27%	33%	37%	31%	25%	33%	32%	29%	23%	47%	30%	35%	31%	51%	9%	38%

Note: Data is as of 2024, except geographic data which is as of 2019. Source: B. S. Bayer Analytics, Morgan Stanley Research

This outlook does not mean low-income or less-educated cohorts will be worse off in absolute terms. Disinflation should still support consumption for these consumers, and wage gains may broaden across industries. In addition, any temporary increase in unemployment could potentially lead to rate cuts, benefitting these consumers who tend to have more short-term and floating rate debt. That said, in order to get a scenario where low-income or less-educated groups are relatively better off, it would likely need to be the case that new jobs created (that we cannot yet conceptualize) lean towards the skills of these cohorts, or certain fiscal policies are put in place that directly benefit these consumers.

Bear Case: Rapid AI diffusion leads to more extreme labor displacement, followed by a demand shock that affects all cohorts

In our bear case, there is a larger spike in unemployment, anywhere from 0.6pp-4.1pp dependent on indirect effects. This increase in unemployment is two-fold: the initial rise is due to a mismatch in skills between workers and available jobs that occurs because of rapid AI diffusion, while a further increase is because of secondary effects of weak demand after the initial shock.

Even in this rapid diffusion bear case scenario, asset market moves are important, as demonstrated by the large range of potential unemployment outcomes. The most severe downturn occurs when initial labor displacement is accompanied by asset market declines. It is also possible a large and persistent enough asset market decline could cause a downturn on its own, without a labor market trigger.

In this bear case, we expect the initial rise in unemployment from displacement would first affect CHIC households, as they are more exposed to AI occupationally. A decline in resources for this group would likely lead them to reduce their discretionary spend. Given the large share of spending these households control, weaker demand from this group would eventually mean the shock spreads beyond those directly exposed. Low exposure occupations tend to be more cyclical, so we expect weak demand would result in higher unemployment for these consumers as well. While the gap between these groups may narrow for a short period, all groups would be left worse off, and monetary and fiscal policy responses will be critical.

Appendix: Tracking Cohort-Level Data

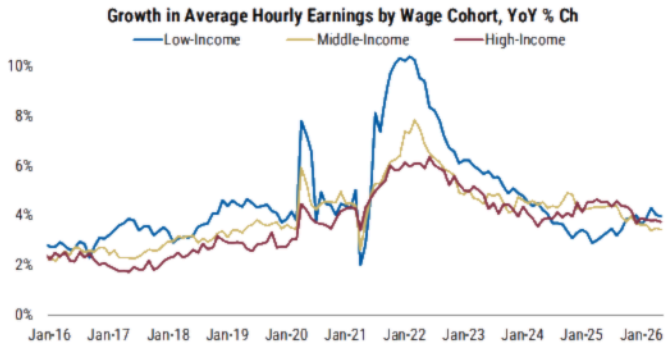
Our base case is only one possible path, so we will track cohort-level data for evidence that outcomes are evolving differently. In this section, we show the cohort-level data we will be tracking on a monthly and quarterly basis to glean how the outlook for different consumer cohorts is changing.

We also highlight two quarterly trackers we are producing related to AI and the economy: 1) our AI labor tracker, which tracks employment and unemployment rate across AI occupation groups, and 2) our AI productivity tracker, which tracks productivity growth across AI industry groups.

Labor Market

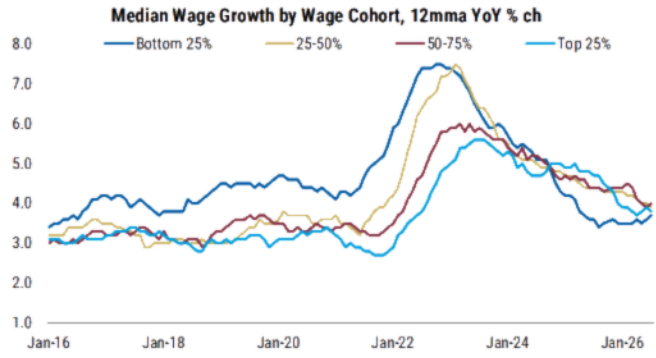
We highlight two measures of wage growth by income cohort. The first is our own calculation (Exhibit 53). For this, we group detailed industries into low-, middle-, and high-income cohorts based on that industry's average earnings from 2019. We then track growth in average hourly earnings across those groups over time. The second is the Atlanta Fed's measure (Exhibit 54). Their measure is built from the household survey, rather than the establishment survey, and tracks the same consumers over time. They then compute each consumer's YoY wage growth and take a 12m moving average of the medians.

Exhibit 53: MS - Wage growth by wage cohort



Source: BLS, Haver Analytics, Morgan Stanley Research

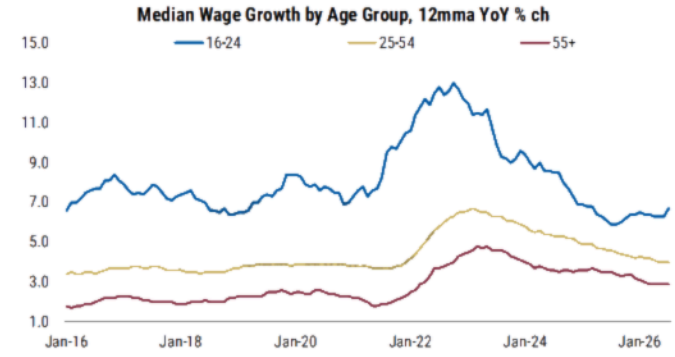
Exhibit 54: Atlanta Fed - Wage growth by wage cohort



Source: Federal Reserve Bank of Atlanta, Haver Analytics, Morgan Stanley Research

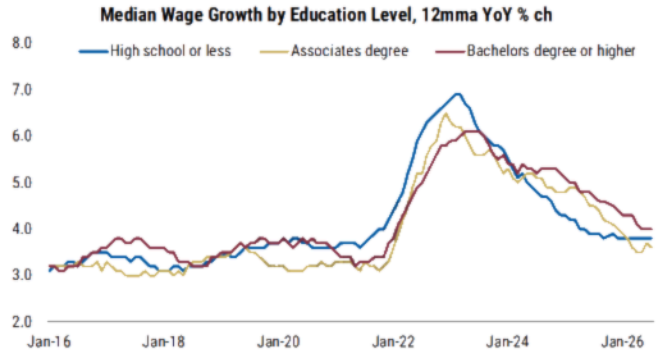
The Atlanta Fed also has wage growth data by age (Exhibit 55) and education level (Exhibit 56), using similar methodology.

Exhibit 55: Wage growth by age group



Source: Federal Reserve Bank of Atlanta, Haver Analytics, Morgan Stanley Research

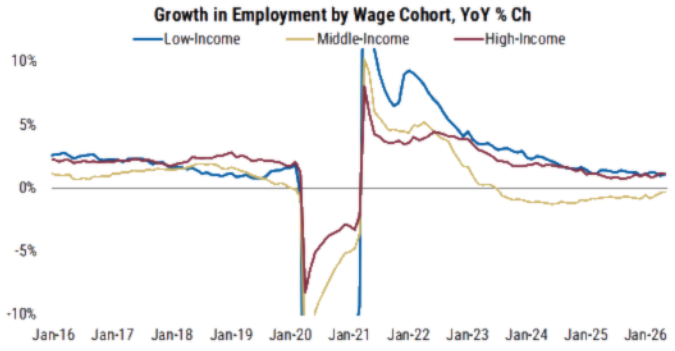
Exhibit 56: Wage growth by education level



Source: Federal Reserve Banks of Atlanta, Haver Analytics, Morgan Stanley Research

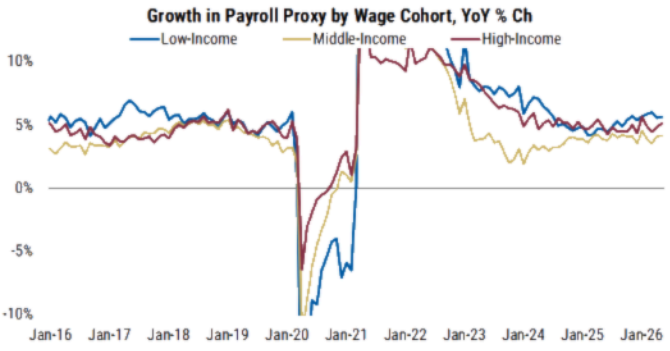
Using our own classifications as in Exhibit 53 above, we look at employment growth by income cohort (Exhibit 57), and a payroll proxy for total labor income (employment*hours worked*average hourly earnings) by cohort (Exhibit 58).

Exhibit 57: Employment growth by wage cohort



Source: BLS, Haver Analytics, Morgan Stanley Research

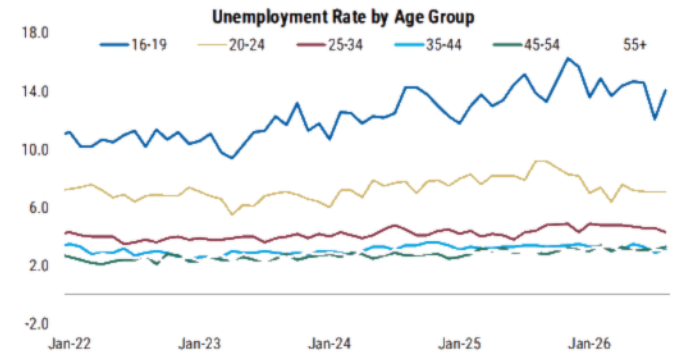
Exhibit 58: Payroll proxy by wage cohort



Source: BLS, Haver Analytics, Morgan Stanley Research

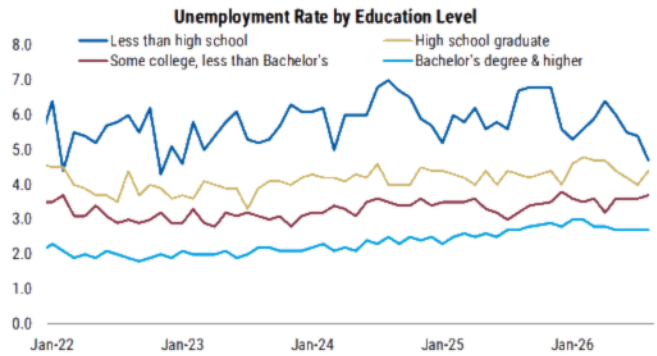
Within the monthly employment report, the household survey also contains data on unemployment rates by age (Exhibit 59) and education level (Exhibit 60). For determining AI effects, we prefer to look at our AI labor tracker linked above, as we control for cyclicality across groups. Still, tracking unemployment rates across cohorts is useful, acknowledging that data at this level of detail tend to be more volatile.

Exhibit 59: Unemployment rates by age group



Source: BLS, Haver Analytics, Morgan Stanley Research

Exhibit 60: Unemployment rates by education level

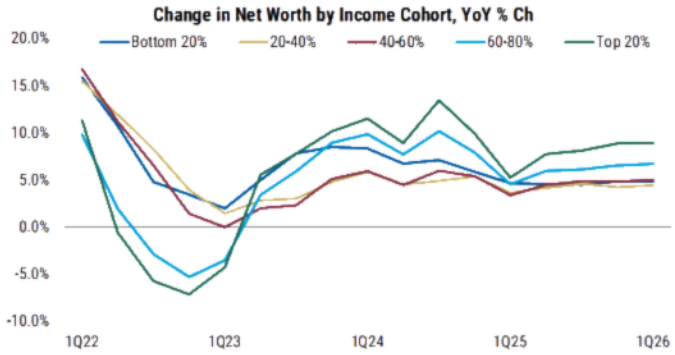


Source: BLS, Haver Analytics, Morgan Stanley Research

Wealth

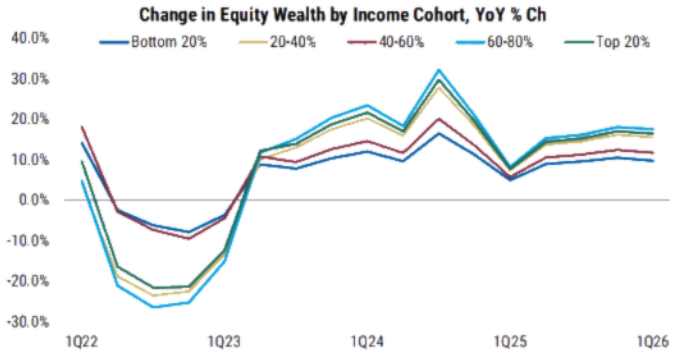
The most frequent measure we use to track household wealth levels is the Fed's Distributional Financial Accounts. In this data, we can track changes in net worth and changes in equity wealth across income, age, and education cohorts, as shown in Exhibit 61 through Exhibit 66 below.

Exhibit 61: YoY change in net worth by income cohort



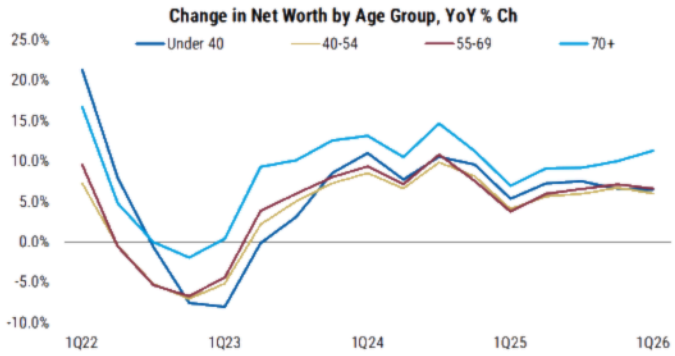
Source: Federal Reserve Board, Haver Analytics, Morgan Stanley Research

Exhibit 62: YoY change in equity wealth by income cohort



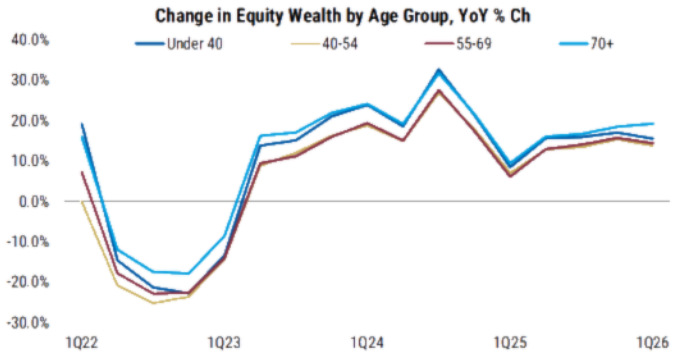
Source: Federal Reserve Board, Haver Analytics, Morgan Stanley Research

Exhibit 63: YoY change in net worth by age group



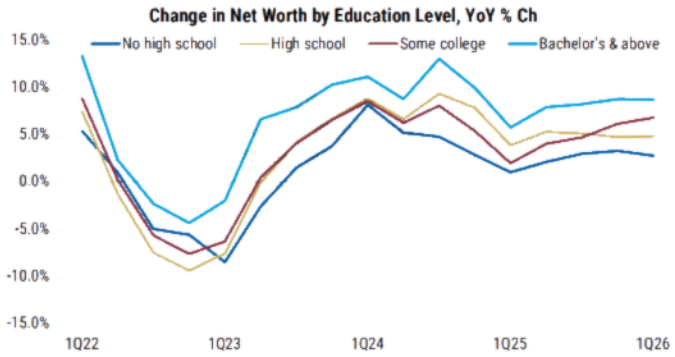
Source: Federal Reserve Board, Haver Analytics, Morgan Stanley Research

Exhibit 64: YoY change in equity wealth by age group



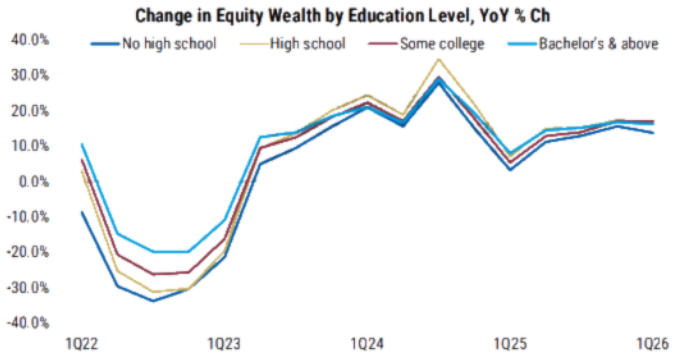
Source: Federal Reserve Board, Haver Analytics, Morgan Stanley Research

Exhibit 65: YoY change in net worth by education level



Source: Federal Reserve Board, Haver Analytics, Morgan Stanley Research

Exhibit 66: YoY change in equity wealth by education level



Source: Federal Reserve Board, Haver Analytics, Morgan Stanley Research

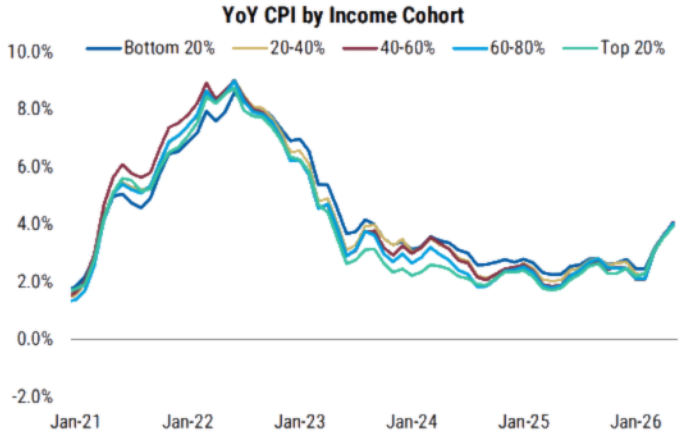
Inflation

There are several sources of data on inflation rates by cohort, but many of them are only

updated annually. We rely on the data produced as part of the Distributional CPI Project, which is of monthly frequency and typically only lagged by a few months. These data estimate experienced CPI for different consumer cohorts, including by income and age cohorts. To do so, they estimate shares of spending across different categories using data from the Consumer Expenditure Survey.

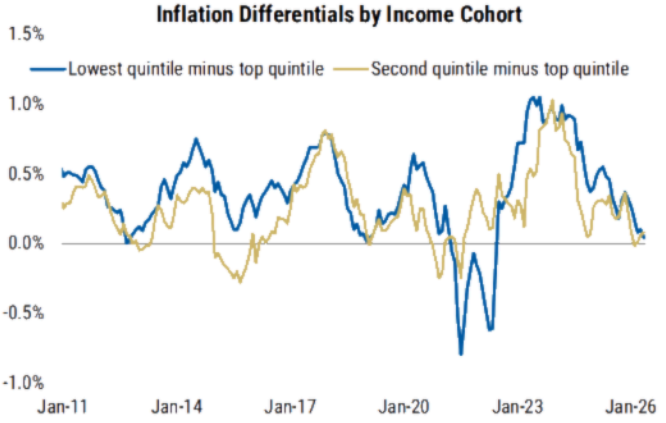
Importantly, a few larger categories that also have large differentials between cohorts mainly drive the inflation gaps. For example, shelter makes up a much larger share of spending for low-income consumers, so the deceleration in shelter inflation over the past few years has contributed to the closing of the gap between the inflation rates of the upper and lower income quintiles. New cars, electricity, gasoline, food (both groceries and restaurants) and airfares are also important drivers.

Exhibit 67: Inflation rates by income cohort



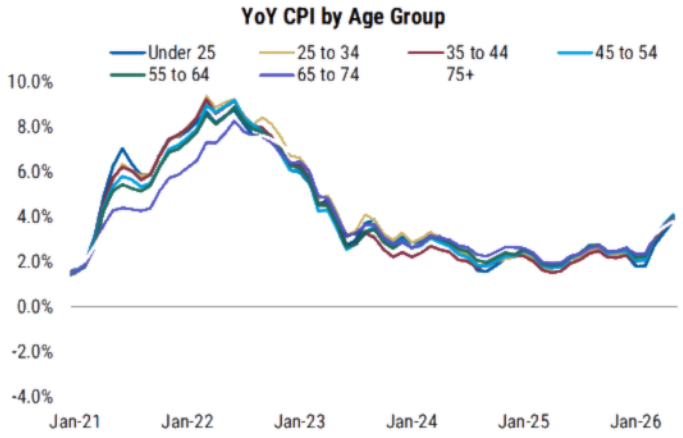
Source: Distributional CPI Project, Morgan Stanley Research

Exhibit 68: Differences between low- and high-income inflation rates



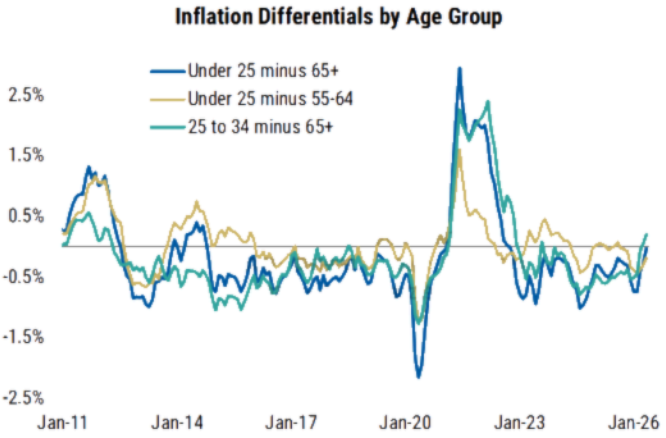
Source: Distributional CPI Project, Morgan Stanley Research

Exhibit 69: Inflation rates by age group



Source: Distributional CPI Project, Morgan Stanley Research

Exhibit 70: Differences between young and old inflation rates



Source: Distributional CPI Project, Morgan Stanley Research

Spending

Frequent data on spending by cohort are harder to find. There are some third-party sources, but we typically rely most on the Consumer Expenditure Survey. This BLS survey details spending across income cohorts, age group, geography, and education level, among

other characteristics. The downside of this data is that it is annual and lagged, with the most recent data still as of 2024. In Exhibit 71 below, we use this data to show cohort spending shares of different categories. Green cells indicate that cohort makes up a relatively larger share of spending in that category, relative to other categories. Red cells indicate that cohort makes up a relatively smaller share of that category.

As we would expect, lower-income consumers make up relatively larger shares of essentials such as groceries, utilities, and shelter, while high-income consumers make up larger shares of insurance/pension spending, education spending, vehicles, and entertainment. Younger consumers make up relatively larger shares of apparel, vehicle, and shelter spending, while older consumers make up larger shares of health care spending. Urban consumers make up larger shares of shelter, apparel, public transport, and education spend, while rural consumers make up larger shares of vehicle and tobacco spending. Finally, the breakdown by education level is similar to that of income cohort. We will track changes in spending across these categories to glean which cohorts could be most affected, and these data are also useful in determining which industries can benefit from certain distributional outcomes.

Exhibit 71: Consumer Expenditure Survey Spending Shares by Cohort (2024)

	All Spending	Groceries	Restuarants	Alcohol	Shelter	Utilities	Furniture	Apparel	Vehicles	Gas	Public Transit (inc airfare)	Health Care	Entertainment	Personal Care	Education	Tobacco	Insurance/ Pension
Income Cohort																	
Bottom 20%	9%	12%	8%	8%	11%	12%	9%	11%	6%	10%	8%	11%	7%	9%	11%	19%	1%
20-40%	13%	16%	12%	11%	15%	17%	12%	13%	11%	15%	8%	16%	12%	13%	9%	20%	6%
40-60%	17%	19%	16%	16%	19%	19%	16%	16%	15%	20%	15%	18%	15%	17%	9%	25%	13%
60-80%	23%	23%	24%	23%	22%	23%	25%	20%	22%	25%	22%	23%	23%	23%	17%	20%	24%
Top 20%	38%	30%	39%	44%	34%	28%	38%	39%	45%	30%	46%	32%	43%	37%	58%	15%	56%
Age Cohort																	
Under 25	3%	3%	4%	3%	4%	2%	3%	4%	4%	3%	3%	1%	3%	3%	8%	3%	2%
25-34	14%	14%	15%	14%	16%	13%	13%	17%	15%	15%	12%	9%	13%	13%	14%	13%	16%
35-44	21%	21%	23%	20%	21%	19%	20%	24%	22%	21%	19%	17%	20%	22%	16%	20%	25%
45-54	21%	20%	21%	21%	19%	20%	18%	21%	20%	23%	21%	18%	22%	20%	33%	21%	25%
55-64	19%	17%	18%	18%	18%	19%	21%	18%	21%	18%	20%	19%	18%	18%	21%	22%	22%
65+	22%	24%	19%	23%	23%	27%	25%	17%	19%	19%	26%	30%	24%	23%	8%	21%	10%
Geography																	
Urban	93%	93%	94%	95%	96%	92%	94%	95%	90%	91%	96%	92%	93%	95%	97%	86%	94%
Rural	6%	7%	6%	5%	4%	8%	6%	5%	10%	9%	4%	8%	7%	5%	3%	14%	6%
Education Level																	
No Degree	37%	44%	35%	29%	38%	47%	38%	36%	38%	48%	23%	40%	32%	36%	17%	72%	28%
Bachelor	31%	28%	31%	32%	31%	29%	29%	30%	33%	29%	30%	31%	32%	32%	33%	19%	34%
Grad	32%	27%	33%	37%	31%	25%	33%	32%	29%	23%	47%	30%	35%	31%	51%	9%	38%

Note: Data is as of 2024, except geographic data which is as of 2019. Source: U.S. Bureau of Labor Analytics, Morgan Stanley Research