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Stock Market Wealth and the Real Economy: A Local Labor Market Approach†

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We provide evidence of the stock market consumption wealth effect by using a local labor market analysis. An increase in local stock wealth driven by aggregate stock prices increases local employment and payroll in nontradable industries and in total, with no effect on employment in tradable industries. In a model of geographic heterogeneity in stock wealth, these responses imply an MPC of 3.2 cents per year and that a 20 percent increase in stock valuations, unless countered by monetary policy, increases the aggregate labor bill by at least 1.7 percent and aggregate hours by at least 0.7 percent two years after the shock. (*JEL* E21, E24, E52, G12, G51, R22, R23)

According to a recent textual analysis of Federal Open Market Committee (FOMC) transcripts by Cieslak and Vissing-Jorgensen (2017), many US policymakers believe that stock market fluctuations affect the labor market through a consumption wealth effect. In this view, a decline in stock prices reduces the wealth of stock-owning households, causing a reduction in spending and hence in employment. While an apparently important driver of US monetary policy, this channel has proved difficult to establish empirically. The main challenge arises because stock prices are forward looking. Therefore, an anticipated decline in future economic fundamentals could also lead to both a negative stock return and a subsequent decline in household spending and employment.

We use a local labor market analysis to address this empirical challenge and provide quantitative evidence on the stock market consumption wealth effect. Our empirical strategy combines regional heterogeneity in stock market wealth with aggregate movements in stock prices. This regional approach identifies the causal effects under weaker assumptions than aggregate time-series analyses, while providing direct evidence that asset prices affect labor market outcomes, which is of

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central interest to policymakers. In addition, our approach appropriately accounts for heterogeneity in marginal propensities to consume (MPC) across households—a feature emphasized in the recent literature—because the regional labor market response already reflects the wealth-weighted average MPC across stockholders in the region. Finally, we develop a heterogeneous area two-agent New Keynesian model that relates the regional outcomes to the household-level MPC out of stock wealth as well as to the aggregate labor market effects of stock wealth changes. Interpreted through this model, our empirical estimates map into a household-level annual MPC of 3.2 cents per dollar of stock wealth and imply that annual aggregate payroll increases by 1.7 percent following a yearly standard deviation increase in the stock market, unless countered by monetary policy.

It helps to begin by describing the consumption wealth effect in our model setting. The environment features a continuum of areas, a tradable good and a nontradable good, stockholders and hand-to-mouth workers, and two factors of production, capital and labor. The only heterogeneity across regions is in their ownership of capital, which also equates to stock wealth. The aggregate price of capital is endogenous and fluctuates due to changes in households' beliefs about the expected *future* productivity of capital. An increase in stock wealth induces areas with greater capital ownership to spend more than the average area. Greater spending in these high wealth areas drives up their labor bill and labor in the nontradable sector and in total. The local labor market boom also (weakly) increases local wages, which induces a (weak) fall in labor in the tradable sector.

In the data, we measure changes in county-level stock market wealth in three steps. In the first step, we capitalize dividend income reported on tax returns aggregated to the county level to arrive at a county-level measure of taxable stock wealth. Our capitalization method improves on existing work such as in Saez and Zucman (2016) by allowing for heterogeneity in dividend yields by wealth, which we obtain using a sample of account-level portfolio holdings from a large discount broker. In the second step, we adjust this measure of taxable stock wealth to account for nontaxable (e.g., retirement) stock wealth, using information on the relationship between taxable and total stock wealth and demographics in the Survey of Consumer Finances. In the final step, we multiply the total county stock wealth with the return on the market (CRSP value-weighted) portfolio and a county-specific portfolio beta constructed from county demographic information and variation in betas across the age distribution in the data from the discount broker. This provides a measure of the change in county stock wealth driven by the aggregate stock return. Motivated by our theoretical analysis, we then divide this change by the county labor bill to arrive at our main regressor.

Our empirical specification identifies the effect of changes in stock wealth on local labor market outcomes by exploiting the substantial variation in the aggregate stock return that occurs independent of other macroeconomic variables. In particular, we allow high wealth areas to exhibit greater sensitivity to changes in aggregate bond wealth, aggregate housing wealth, and aggregate labor income and noncorporate business income, and also control for county fixed effects, state-by-quarter fixed effects, and a Bartik-type industry employment shift-share. Our identifying assumption is that, conditional on these controls, areas with high stock market wealth do not experience unusually rapid employment or payroll growth following a positive aggregate stock return for reasons other than the stock market wealth effect on local spending.

An increase in local stock wealth induced by a positive stock return increases total local employment and payroll. Seven quarters after an increase in stock market wealth equivalent to 1 percent of local labor market income, local employment is 0.77 basis points higher and local payroll is 2.18 basis points higher. Because stock returns are nearly i.i.d., these responses reflect the short-run effect of a permanent change in stock market wealth. Motivated by the theory, we also investigate the effect on employment and the labor bill in the nontradable and tradable industries, following the sectoral classifications in Mian and Sufi (2014). Consistent with the theory, the employment response in nontradable industries exceeds the overall response, while employment in tradable industries does not increase. We also report a large response in the residential construction sector, consistent with a household demand channel.

The main threat to a causal interpretation of these findings is that high wealth areas respond differently to other aggregate variables that co-move with the stock market. This concern motivates the variables included in our baseline specification. The absence of "pre-trend" differences in outcomes in the quarters before a positive stock return and the non-response of employment in the tradable sector support a causal interpretation of our findings. We report additional robustness along a number of dimensions, including (i) using a more parsimonious specification that excludes the parametric controls; (ii) interactions of stock market wealth with TFP growth to allow wealthier counties to have different loadings on this variable; (iii) controlling for local house prices; (iv) using only within commuting zone variation in stock market wealth; (v) subsample analysis, including dropping the wealthiest counties and the quarters with the most volatile stock returns; and (vi) not weighting the regression. A decomposition along the lines of Andrews, Gentzkow, and Shapiro (2017) shows that no single state drives the results. We also report a quantitatively similar response using cross-state variation and state-level consumption expenditure from the Bureau of Economic Analysis.

Our baseline analysis assumes a homogeneous treatment effect across areas. A natural question concerns what this specification identifies in the presence of possible MPC heterogeneity across households—as in a growing literature that emphasizes liquidity constraints or behavioral frictions. An advantage of a regional approach is that it already reflects the wealth-weighted average MPC in a region. Because stock wealth heterogeneity is substantially greater within than across counties, this means that the cross-county regression approximately reflects the wealth-weighted average MPC across *all* stockholders—the MPC that matters for *aggregate* stock wealth fluctuations. We substantiate this result quantitatively in a Monte Carlo exercise on simulated data that matches the empirical distributions of stock market participation and stock wealth across households and the cross-county distribution of average stock wealth.

We combine our empirical results with the theoretical model to calibrate two key parameters: the household-level stock wealth effect and the degree of local wage adjustment. To calibrate the stock wealth effect, we provide a separation result from our model that decomposes the empirical coefficient on the *nontradable* labor bill into the product of three terms: the household-level marginal propensity to consume out of stock market wealth, the local Keynesian multiplier (equivalent to the multiplier on local government spending), and the labor share of income.[1] This decomposition applies to more general changes in local consumption demand and therefore may be of use outside our particular setting. We use standard values from previous literature to calibrate the labor share of income and the local Keynesian multiplier. Given these values, the empirical response of the nontradable labor bill implies that in partial equilibrium a one dollar increase in stock-market wealth increases annual consumption expenditure by about 3.2 cents two years after the shock. For the degree of wage adjustment, comparing the response of total employment with the response of the total labor bill suggests that a 1 percent increase in labor (total hours worked) is associated with a 0.9 percent increase in wages at a two year horizon.

Finally, we use the model to quantify the *aggregate* effects that stock price shocks would generate if monetary policy (or other demand-stabilization policies) did not respond to the shock. We first show that a one dollar increase in stock market wealth has the same *proportional* effect on the *local nontradable* and *aggregate total* labor bills, up to an adjustment for the difference in the local and aggregate spending multipliers. This result does not depend on the particular calibration of the direct household-level wealth effect just described. It does require homothetic preferences and production across the nontradable and tradable sectors, and we provide evidence in support of this assumption at the level of the broad sectoral groupings we use in the data. Next, we show how the local response of wages informs about the aggregate wage Phillips curve in our model. Since labor markets are local, the aggregate wage response is similar to the local wage response, with an adjustment due to the fact that demand shocks impact aggregate inflation and local inflation differently. We then consider a 20 percent positive shock to stock valuations—approximately the yearly standard deviation of stock returns. Using our empirical estimate for the nontradable labor bill, and applying a bounding argument for moving from local to aggregate effects similar to that in Chodorow-Reich (2019), this shock would increase the aggregate labor bill by at least 1.7 percent two years after the shock. Combining this effect with the degree of aggregate wage adjustment implied by our local estimates, the shock would also increase aggregate hours by at least 0.7 percent.

The rest of the paper proceeds as follows. After discussing the related literature, we present the empirical analysis. Section I describes the datasets and the construction of our main variables. Section II details the baseline empirical specification and discusses conditions for causal inference. Section III contains the empirical results. We then turn to the theoretical analysis and the structural interpretation. Section IV describes our model. Section V uses the empirical results to calibrate the model and derive the household-level wealth effect. Section VI calculates the implied aggregate wealth effects, and Section VII concludes.

Related Literature.—Our paper contributes to a large literature that investigates the relationship between stock market wealth, consumption, and the real economy.

[1] In general, there may be an additional term reflecting the response of output in the tradable sector when relative prices change across areas. This term disappears in our benchmark calibration, which features Cobb-Douglas preferences across tradable goods produced in different regions. Allowing for a non-unitary elasticity of substitution across regions does not meaningfully change our conclusions.

A major challenge is to disentangle whether the stock market has an effect on consumption over a relatively short horizon (the direct wealth effect), or whether it simply predicts future changes in productivity, income, and consumption (the leading indicator effect). The challenge is compounded by the scarcity of datasets that contain information on household consumption and financial wealth. The recent literature has tried to address these challenges in various ways (see Poterba (2000) for a survey of the earlier literature).

The literature using aggregate time series data finds mixed evidence (see e.g., Poterba and Samwick 1995; Davis and Palumbo 2001; Ludvigson, Steindel, and Lettau 2002; Lettau and Ludvigson 2004; Carroll, Otsuka, and Slacalek 2011). Davis and Palumbo (2001) and Carroll, Otsuka, and Slacalek (2011) estimate a wealth effect of up to around 6 cents. On the other hand, Lettau and Ludvigson (2004) argue for more limited wealth effects. However, an aggregate time series approach introduces two complications: First, in an environment in which monetary policy effectively stabilizes aggregate demand fluctuations, as in our model, there can be strong wealth effects and yet no relationship between asset price shocks and aggregate consumption. Second, stock market fluctuations may affect aggregate demand via an investment channel (see Cooper and Dynan 2016 for other issues with using aggregate time series in this context).

Another strand of the literature uses household level data and exploits the heterogeneity in household wealth to isolate the stock wealth effect. Dynan and Maki (2001) use Consumer Expenditure Survey (CE) data to compare the consumption response of stockholders with non-stockholders. They find a relatively large marginal propensity to consume (MPC) out of stock wealth—around 5 to 15 cents per dollar per year. However, Dynan (2010) re-examines the evidence by extending the CE sample to 2008 and finds weaker effects. More recently, Di Maggio, Kermani, and Majlesi (2020) use detailed individual-level administrative wealth data for Sweden to identify the stock wealth effect from variation in individual-level portfolio returns. They find substantial effects; the top 30 percent of the income distribution, who own most of the stocks, have an estimated MPC of around 3 cents per dollar per year.[2]

We complement these studies by focusing on *regional* heterogeneity in stock wealth. We show how the regional empirical analysis can be combined with a model to estimate the household-level stock wealth effect. The MPC implied by our analysis (3.2 cents per dollar per year) is close to estimates from the recent literature. An important advantage of our approach is that it directly estimates the local *general equilibrium* effect. In particular, by examining the labor market response, we provide direct evidence on the margin most important to monetary policymakers.

Case, Quigley, and Shiller (2005) and Zhou and Carroll (2012) also use regional variation to estimate financial wealth effects. Case, Quigley, and Shiller (2005) overcome the absence of geographic data on financial wealth by using state-level mutual fund holdings data from the Investment Company Institute (ICI) and measure state consumption using retail sales data from the Regional Financial Associates. Zhou and Carroll (2012) criticize the data construction and empirical specification in

[2] See also Bostic, Gabriel, and Painter (2009) and Paiella and Pistaferri (2017) for similar analyses of stock wealth effects in different contexts.

Case, Quigley, and Shiller (2005) and construct their own dataset using proprietary data on state-level financial wealth and retail sales taxes as a proxy for consumption. Both papers find negligible stock wealth effects and a sizable housing wealth effect. Relative to these papers, we exploit the much greater variation in financial wealth across counties than across states and provide evidence on the labor market margin directly. Other recent papers use regional variation but focus only on estimating housing wealth effects (Mian, Rao, and Sufi 2013; Mian and Sufi 2014; Guren et al. 2020b).[3]

Our estimate for the household-level MPC out of stock market wealth is broadly in line with the quantitative predictions from frictionless models such as the permanent income hypothesis, but considerably smaller than the estimated MPCs out of liquid income found in the recent literature (Parker et al. 2013), even among higher income households (Kueng 2018; Fagereng, Blomhoff, and Natvik 2019). One interpretation is that households that hold stock wealth are affected relatively less by borrowing constraints or by behavioral frictions that increase MPCs. Another possibility is that these households are subject to similar frictions as other households, but stock wealth is associated with more severe transaction costs (such as tax frictions or information frictions) that lead to lower MPCs than other types of liquid income. The latter view is consistent with recent evidence from Di Maggio, Kermani, and Majlesi (2020), who argue that Swedish households respond to capital gains significantly less than they respond to dividend payouts.

Our focus on the consumption wealth channel complements research on the investment channel of the stock market that dates to Tobin (1969) and Hayashi (1982). Under the identifying assumptions we articulate below, our local labor market analysis absorbs the effects of changes in Tobin's q or the cost of equity financing on investment into a time fixed effect, allowing us to isolate the consumption wealth channel.

Our theoretical framework builds upon the model in Mian and Sufi (2014) by incorporating several features important for a structural interpretation of the results, including endogenous changes in wealth, monetary policy, partial wage adjustment, households with heterogeneous MPCs, and imperfectly substitutable tradable goods. Our framework also shares features with models of small open economies with nominal rigidities (e.g., Gali and Monacelli 2005) adapted to the analysis of monetary unions by Nakamura and Steinsson (2014) and Farhi and Werning (2016), but differs from these papers by including a fully nontradable sector. This feature facilitates the structural interpretation and aggregation of the estimated local general equilibrium effects.

Our structural interpretation and aggregation results represent methodological contributions that apply beyond our particular model. First, and similar to the approach in Guren et al. (2020b) and formalized in Guren et al. (2020a), we illustrate

[3] See also, Case, Quigley, and Shiller (2005, 2011); Campbell and Cocco (2007); Mian and Sufi (2011); Carroll, Otsuka, and Slacalek (2011); and Browning, Gørtz, and Leth-Petersen (2013), among others. In terms of comparison of wealth effects from stock wealth versus housing wealth, Guren et al. (2020b) estimate an MPC out of housing wealth of around 2.7 cents during 1978–2017, which is comparable in magnitude to our estimate of the stock wealth effect. This is substantially lower than the estimates in Mian, Rao, and Sufi (2013) and Mian and Sufi (2014), which are in the range of 7 cents. See Guren et al. (2020b) for a discussion of the possible drivers of these differences.

how the estimated local general equilibrium effects can be combined with external estimates of the local income multiplier (e.g., estimates from local government spending shocks) to obtain the direct household-level spending effect.[4] Our decomposition differs from theirs in that it applies to the coefficient for the nontradable labor bill—a variable that is easily observable at the regional level—and therefore includes an adjustment for the labor share of income. Second, we show how, under standard assumptions, the response of the local labor bill in the *nontradable* sector provides a direct and transparent bound for the response of the aggregate effect across *all* sectors when monetary policy does not react.

I. Data

In this section we explain how we measure the key objects in our empirical analysis: the ratio of geographic stock market wealth to labor income, the stock market return, employment, and payroll. Our geographical unit is a US county. This level of aggregation leaves ample variation in stock market wealth while being large enough to encompass a substantial share of spending by local residents. The United States contains 3,142 counties using current delineations. Table A.4 in the online Appendix reports summary statistics for the variables described next.

A. *Stock Market Wealth*

We denote our main regressor as $S_{a,t-1} R_{a,t-1,t}$, where $S_{a,t-1}$ is stock market wealth in county a in period $t-1$ normalized by the period $t-1$ labor bill and $R_{a,t-1,t}$ is the portfolio return between $t-1$ and t. In Section IV, we show that regressions of log changes in local labor market outcomes on this variable yield coefficients tightly related to the key parameters of our model.

We construct local stock market wealth by capitalizing taxable dividend income and then adjusting for stock wealth held in nontaxable accounts. We summarize our methodology here and provide additional detail of the data, sample construction, and adjustments in online Appendix A.1. Our capitalization method involves multiplying observed taxable dividend income by a price-dividend ratio to arrive at stock wealth held in taxable accounts.[5] We start with IRS Statistics of Income (SOI) data containing county aggregates of annual dividend income reported on individual tax returns, over the period 1989–2015. Dividend income as reported on form 1040 includes any distribution from a C-corporation. It excludes distributions from partnerships, S-corporations, or trusts, except in rare circumstances

[4] In contemporaneous work, Wolf (2019) formally establishes (in a closed economy setting) conditions under which the multiplier effects from private spending are exactly the same as the multiplier effects from public spending.

[5] The literature has proposed other income measures and capitalization factors. Mian, Rao, and Sufi (2013) and Mian and Sufi (2014) group dividends, interest, and other non-wage income together and use the ratio of total household financial wealth in the Financial Accounts of the United States (FAUS) to the national aggregate of this combined income measure as a single capitalization factor for all financial wealth. Saez and Zucman (2016) and Smith, Zidar, and Zwick (2020) use both dividends and capital gains to allocate directly held corporate equities in the FAUS, with Smith, Zidar, and Zwick arguing forcefully for a low weight on the capital gains component because realized capital gains include many transactions other than sales of corporate equity. Relative to these alternatives, capitalizing dividends using a price-dividend ratio isolates the income stream most closely related to corporate equity wealth and facilitates the adjustment for heterogeneous dividend yields described below.

where S-corporations that converted from C-corporations distribute earnings from before their conversion. While we cannot separate distributions from publicly traded and privately held C-corporations, we show in online Appendix A.1.4 that equity in privately held C-corporations is too small (less than 7 percent of total equity of C-corporations) to meaningfully affect our results.

We construct a county-specific capitalization factor as the product of the price-dividend ratio on the value-weighted CRSP portfolio and a time-varying county-specific adjustment. The CRSP portfolio contains all primary listings on the NYSE, NYSE MKT, NASDAQ, and Arca exchanges and, therefore, covers essentially the entire US equity market. The county-specific adjustment recognizes that older individuals both have higher average wealth and hold higher dividend-yield stocks, as first conjectured in Miller and Modigliani (1961) and documented in Graham and Kumar (2006). We believe we are the first to apply such an adjustment in capitalizing equity wealth. To do so, we follow Graham and Kumar (2006) and use the Barber and Odean (2000a, b) dataset of individual account-level stock holdings from a large discount broker over the period 1991–1996.[6] Specifically, as we describe in more detail in online Appendix A.1.2, we merge the Barber and Odean (2000b) dataset with CRSP stock and mutual fund data and compute average dividend yields for five age groups, separately for each census region. The dividend yield slopes upward with age, with individuals 65 and over holding stocks with a dividend yield about 10 percent (*not* p.p.) higher than the market average and individuals 35 and younger holding stocks with a dividend yield about 10 percent lower than the market average. Importantly, variation by age accounts for essentially all of the variation in dividend yields across the wealth distribution, as shown in Figure A.1 and Table A.1 in the online Appendix. We combine the age-specific dividend yields with county-level demographic information and wealth by age group from the Survey of Consumer Finances (SCF). We then adjust the CRSP dividend yield in each county-year by the age-wealth-weighted average of the age-specific dividend yields.

We next adjust county taxable stock market wealth to account for wealth held in nontaxable accounts, primarily in defined contribution pension plans.[7] We do not include wealth in defined benefit pension plans, since household claims on that wealth do not fluctuate directly with the value of the stock market. Roughly one-third of total household stock market wealth is held in nontaxable accounts (see online Appendix Figure A.4). In online Appendix A.1.3, we estimate the relationship at the household level between total stock market wealth, taxable stock market wealth, and household demographic characteristics, using the SCF. Total and taxable stock market wealth vary almost one-to-one, reflecting statutory limits on contributions to nontaxable accounts that make nontaxable wealth much more evenly distributed than taxable wealth. The variables also explain total wealth

[6] The data are a random sample of accounts at the brokerage and have been used extensively to study individual trading behavior (Barber and Odean 2000b, 2001; Graham and Kumar 2006; Barber and Odean 2008; Mitton and Vorkink 2007; Kumar 2009; Seasholes and Zhu 2010; Kent, Garlappi, and Xiao 2019). Graham and Kumar (2006) compare the data with the 1992 and 1995 waves of the SCF and show that the stock holdings of investors in the brokerage data are fairly representative of the overall population of retail investors. We consider taxable accounts with at least one dividend-paying stock to mimic the dividends observed in the IRS data.

[7] This adjustment is appropriate if the marginal propensities to consume out of taxable and nontaxable stock wealth are the same. We revisit this assumption at the end of our analysis (see footnote 41).

well, with an R^2 above 0.9. We combine the coefficients on taxable wealth and demographic characteristics from the SCF with our county-level measure of taxable stock wealth and county-level demographic characteristics to produce our final measure of total county stock market wealth. Finally, we divide this measure by SOI (annual) county labor income to arrive at our measure of local stock market wealth relative to labor income, $S_{a,t}$.

B. *Stock Market Return*

We write the stock market return in county a as $R^*_{a,t-1,t} = \alpha_a + R^f_{t-1,t} + b_{a,t} \times (R^m_{t-1,t} - R^f_{t-1,t}) + e_{a,t-1,t}$, where $R^f_{t-1,t}$ is the risk-free rate in period t, $R^m_{t-1,t}$ is the market return, $b_{a,t}$ is a county-specific portfolio beta, and $e_{a,t-1,t}$ is an idiosyncratic component of the return. We do not observe $R^*_{a,t-1,t}$. Instead, we define the variable $R_{a,t-1,t}$ that enters into our main regressor as $R_{a,t-1,t} = R^f_{t-1,t} + b_{a,t} \times (R^m_{t-1,t} - R^f_{t-1,t})$. To operationalize $R_{a,t-1,t}$, we equate the risk-free rate $R^f_{t-1,t}$ with the interest rate on a 3-month Treasury bill, the market return $R^m_{t-1,t}$ with the total return on the value-weighted CRSP portfolio, and construct the county-specific portfolio beta $b_{a,t}$ using the relationship between market beta and age in the Barber and Odean (2000b) dataset and our measure of the county age-wealth distribution. This adjustment incorporates the tendency for older, wealthier households to hold stocks with lower betas, a pattern we document in Figure A.6 of the online Appendix. Ignoring it would result in systematic over-counting of changes in wealth in high wealth areas when the stock market changes, leading to an under-estimate of the consumption wealth effect, although this effect turns out to be small in practice as the $b_{a,t}$ all lie between 0.97 and 1.03.

We now discuss the differences between the true county return $R^*_{a,t-1,t}$ and the measured return $R_{a,t-1,t}$ and why these differences do not affect the validity of our empirical analysis. Three possible differences exist. First, the true county return includes a county-specific α_a, reflecting differences in portfolio characteristics and the possibility that high wealth areas have systematically better portfolios, as suggested by Fagereng et al. (2016). Our empirical specification will include county fixed effects to absorb permanent heterogeneity along this dimension.[8] Second, high wealth areas could have systematically riskier or less risky stock portfolios beyond the correlation due to age, in which case we would systematically mis-measure $b_{a,t}$. While previous work has documented that wealthy households have portfolios tilted toward riskier asset classes than the general population (Carroll 2002, Calvet and Sodini 2014), here what matters is risk-taking *within* stock portfolios. Figure A.6 in the online Appendix shows this correlation using the Barber and Odean (2000b) dataset. Except for the bottom wealth decile, who typically hold only one or two securities and have very low beta portfolios, there is a nearly flat relationship between beta and wealth decile within age bins. Therefore, this source of heterogeneity does not appear important in practice. Third, the true return $R^*_{a,t-1,t}$ contains an idiosyncratic component $e_{a,t-1,t}$, reflecting differences in portfolio allocation arising, for example, from home bias as documented in Coval and Moskowitz (1999)

[8] While the fixed effect absorbs permanent heterogeneity, in fact wealth is highly persistent over time, with a within-state correlation between $S_{a,1990}$ and $S_{a,2015}$ of 0.81.

or from differences in market beta uncorrelated with wealth. This component has no impact on our empirical results because it gives rise to idiosyncratic changes in wealth that are uncorrelated with our main regressor. This statement remains true even if the idiosyncratic part of the return correlates with local economic activity, as might occur due to home bias in portfolio allocation.[9]

Figure 1, panel A shows the serial correlation in the quarterly return on the CRSP portfolio and Figure 1, panel B the cumulative return following a one standard deviation increase in the stock market during our sample period. As is well known, stock returns are nearly i.i.d., a result confirmed by the almost complete absence of serial correlation in Figure 1, panel A. This pattern facilitates interpretation of our empirical results since it implies that a stock return in period t has a roughly permanent effect on wealth, and we mostly ignore the small momentum and subsequent reversal shown in Figure 1, panel B in what follows. Figure 1, panel C shows the correlation of the period t stock return with the changes in other macroeconomic aggregate variables over the horizon $t-1$ to $t+h$. In our sample, the stock market return is positively correlated with aggregate labor income and house prices, and negatively correlated with fixed income returns. However, the correlation coefficients are all well below one, reflecting the substantial movement in stock prices independent of these other factors (Shiller 1981, Cochrane 2011, Campbell 2014).

C. *Outcome Variables*

Our main outcome variables are log employment and payroll from the Bureau of Labor Statistics Quarterly Census of Wages and Employment (QCEW). The source data for the QCEW are quarterly reports filed with state employment security agencies by all employers covered by unemployment insurance (UI) laws. The QCEW covers roughly 95 percent of total employment and payroll, making the dataset a near universe of administrative employment records. We use the NAICS-based version of the data, which start in 1990, and seasonally adjust the published county-level data by sequentially applying Henderson filters using the algorithm contained in the Census Bureau's X-11 procedure.[10]

An important element of our analysis is to distinguish between responses in sectors affected by local demand shocks, which we refer to as "nontradable" sectors,

[9]Formally, assume the true structural model is $y_a = \beta(S_a R_a^*) + \epsilon_a$ and $R_a^* = R_a + e_a$, where y_a is an outcome, e_a is a mean-zero component of the return independent of wealth S_a or the measured part of the return R_a, and the structural residual ϵ_a is independent of the measured change in wealth $S_a R_a$. (We have dropped time subscripts and ignored the component α_a to simplify notation and without loss of generality). Substituting, we have $y_a = \beta(S_a R_a) + u_a$, where $u_a = \beta S_a e_a + \epsilon_a$ is a composite residual. Therefore, the coefficient $\hat{\beta}$ from regressing y_a on $S_a R_a$ asymptotes to β, since $\mathrm{cov}(S_a e_a, S_a R_a) = \mathrm{cov}(\epsilon_a, S_a R_a) = 0$ by the independence assumptions on e_a and ϵ_a. Alternatively, one can think of $S_{a,t-1} R_{t-1,t}$ as the excluded instrument and $S_{a,t-1} R_{a,t-1,t}^*$ as the endogenous variable in an instrumental variables design. Under the assumption of purely idiosyncratic heterogeneity, the first stage regression of $S_{a,t-1} R_{a,t-1,t}^*$ on $S_{a,t-1} R_{t-1,t}$ would yield a coefficient of 1, in which case the IV coefficient coincides with the reduced form coefficient that we estimate. Importantly, this argument extends straightforwardly to mis-measurement of $S_{a,t}$ due to heterogeneity in the price-dividend ratio uncorrelated with true wealth. Finally, the argument makes no assumption on the correlation between the idiosyncratic component of the return e_a and the structural residual ϵ_a, as might occur in the context of home bias in portfolio allocation. Hyslop and Imbens (2001) provide a more general discussion of measurement error that does not lead to biased estimation.

[10]The NAICS version of the QCEW contains a number of transcription errors prior to 2001. We follow Chodorow-Reich and Wieland (2020, Appendix F) and hand-correct these errors before applying the seasonal adjustment procedure.

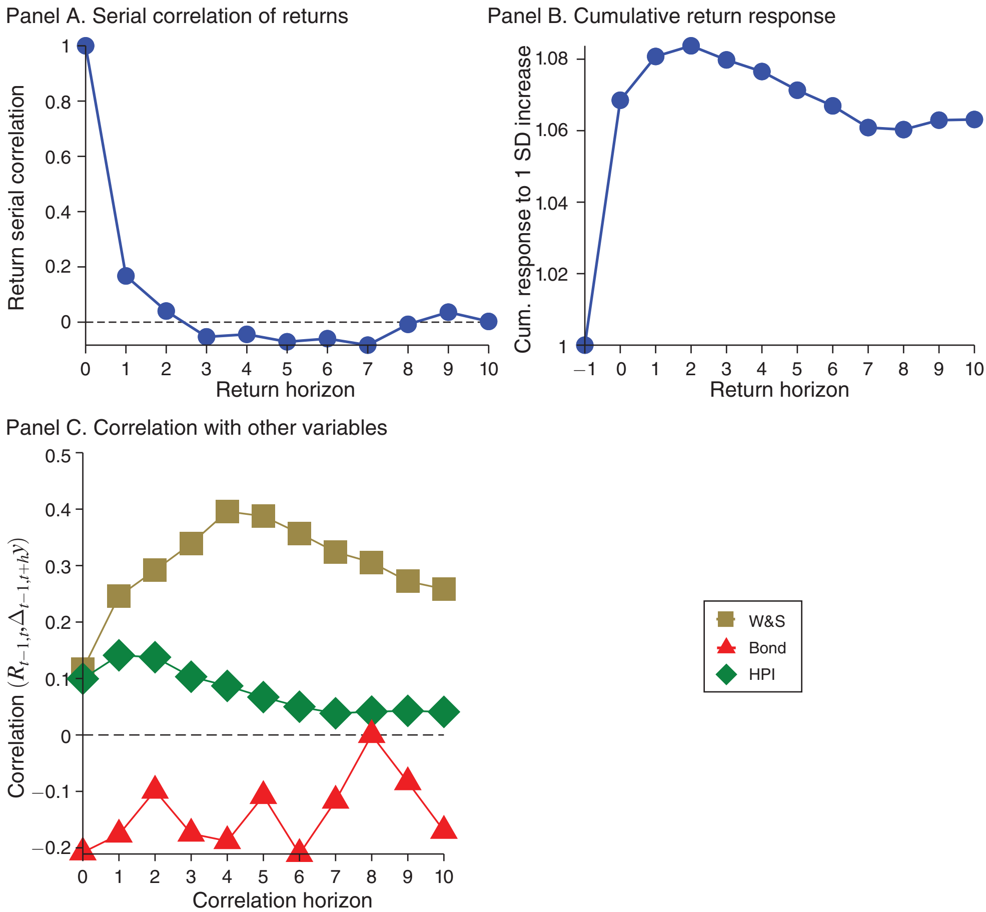

Figure 1. Attributes of Quarterly Stock Returns

Notes: Panel A reports the coefficients β_h from estimating the regression $R_{t+h-1,t+h} = \alpha_h + \beta_h R_{t-1,t} + e_h$ at each quarterly horizon h shown on the lower axis, where $R_{t+h-1,t+h}$ is the total return on the value-weighted CRSP portfolio between quarters $t + h - 1$ and $t + h$. Panel B reports the transformation $\prod_{h=0}^{j}(1 + \beta_h \sigma_R)$ at each quarterly horizon j shown on the lower axis, where σ_R is the standard deviation of the CRSP return. Panel C reports the correlation coefficients of $R_{t-1,t}$ and $y_{t-1,t+h}$ at each quarterly horizon h shown on the lower axis, where $y_{t-1,t+h}$ is the log change in aggregate labor compensation, the holding return on the 5-year Treasury, or the change in aggregate house prices between $t - 1$ and $t + h$.

and "tradable" sectors unlikely to be affected by local demand shocks. We follow Mian and Sufi (2014) and label NAICS codes 44–45 (retail trade) and 72 (accommodation and food services) as nontradable and NAICS codes 11 (agriculture, forestry, fishing and hunting), 21 (mining, quarrying, and oil and gas extraction), and 31–33 (manufacturing) as tradable.[11] The retail trade sector includes a wide variety of establishments that cover essential (e.g., grocery stores, drug stores) and luxury (e.g., specialty food stores, jewelry stores) expenditure and everything in between

[11] Mian and Sufi (2014) exclude NAICS 721 (accommodation) from their definition of nontradable industries. We leave this industry in our measure to avoid complications arising from the much higher frequency of suppressed data in NAICS 3 than NAICS 2 digit industries in the QCEW data. The national share of nontradable employment and payroll in NAICS 721 are both less than 8 percent and we have verified using counties with non-suppressed data that including this sector does not affect the nontradable responses reported below.

(e.g., auto dealers, furniture stores, clothing stores). Nonetheless, this classification is conservative in the sense that it leaves a large amount of employment unclassified. This is in line with our model calibration, which depends only on having a subset of industries that produce truly nontradable goods. On the other hand, even most manufacturing shipments occur within the same zip code (Hillberry and Hummels 2008), which suggests local consumption demand could impact our measure of tradables. We report robustness to using a classification scheme based on the geographic concentration of employment in an industry.

II. Econometric Methodology

This section provides a formal discussion of causal identification, presents our baseline specification, and discusses the main threats to identification.

A. *Framework*

Motivated by the model in Section IV, we assume a true data generating process of the form

$$(1)\qquad \Delta_{a,t-1,t+h}y = \beta_h\big[S_{a,t-1}R_{a,t-1,t}\big] + \Gamma_h' X_{a,t-1} + \epsilon_{a,t-1,t+h},$$

where $\Delta_{a,t-1,t+h}y = y_{a,t+h} - y_{a,t-1}$ is the change in variable y in area a between $t-1$ and $t+h$, $S_{a,t-1}$ is stock market wealth in area a in period $t-1$ relative to labor market income in the area, $R_{a,t-1,t} = b_{a,t}R^m_{t-1,t} + (1-b_{a,t})R^f_{t-1,t}$ is the measured return on the stock portfolio, $X_{a,t-1}$ collects included covariates determined (from the perspective of a local area) as of time $t-1$, β_h and Γ_h are coefficients (with the latter possibly vector-valued), and $\epsilon_{a,t-1,t+h}$ contains unmodeled determinants of the outcome variable. We will discuss identification of β_h under the maintained assumption of a homogenous treatment effect across areas. We explore treatment heterogeneity explicitly in Section IIID and argue there that the county-level specification will approximately reflect the wealth-weighted average MPC out of stock wealth even if this MPC varies across individuals with the level of stock wealth.

Let $\hat{\beta}_h$ and $\hat{\Gamma}_h$ denote the coefficients from treating $\epsilon_{a,t-1,t+h}$ as unobserved and equation (1) as a Jordà (2005) local projection to be estimated by OLS. Because the local portfolio betas $\{b_{a,t}\}$ all lie close to 1, and $R^f_{t-1,t}$ is much less volatile than $R^m_{t-1,t}$, we can use the approximation $S_{a,t-1}R_{a,t-1,t} \approx S_{a,t-1}b_{a,t}R^{\,m}_{t-1,t}$ in equation (1).[12] In that case, equation (1) has an approximate shift-share structure with a single national shifter given by the market return $R^m_{t-1,t}$, and the identifying assumption for $p\lim\hat{\beta}_h = \beta_h$ takes the form

$$(2)\qquad E\big[R^m_{t-1,t}\mu_t\big] = 0,$$

[12]That is, for any (de-meaned) variable $v_{a,t}$, $E[S_{a,t-1}R_{a,t-1,t}v_{a,t}] = E[S_{a,t-1}b_{a,t}R^m_{t-1,t}v_{a,t}] + E[S_{a,t-1}(1-b_{a,t})R^f_{t-1,t}v_{a,t}] \approx E[S_{a,t-1}b_{a,t}R^m_{t-1,t}v_{a,t}]$, where the term $E[S_{a,t-1}(1-b_{a,t})R^f_{t-1,t}v_{a,t}]$ is negligible because $1-b_{a,t} \approx 0$ and $\mathrm{var}(R^f_{t-1,t}) \ll \mathrm{var}(R^m_{t-1,t})$. In fact, our results below change imperceptibly whether or not we include the term $S_{a,t-1}(1-b_{a,t})R^f_{t-1,t}$.

where $\mu_t \equiv E[S_{a,t-1} b_{a,t} \epsilon_{a,t-1,t+h}]$ is a time t cross-area average of the product of the beta-adjusted stock wealth-to-income $b_{a,t} S_{a,t-1}$ and the unobserved component $\epsilon_{a,t-1,t+h}$.[13] Intuitively, this condition will not hold if the outcome variable (e.g., employment or payroll) grows faster for unmodeled reasons ($\epsilon_{a,t-1,t+h} > 0$) in high wealth areas ($\Rightarrow \mu_t > 0$) in periods when the stock return is positive, and vice versa when the stock return is negative.

The econometrics of shift-share designs have recently received renewed attention in Goldsmith-Pinkham, Sorkin, and Swift (2018) and Borusyak, Hull, and Jaravel (2018). Equation (2) coincides with the exogeneity condition in Borusyak, Hull, and Jaravel (2018) in the case of a single national observed shock and multiple (asymptotically infinite) areas and time periods. As in their framework, the condition recasts the identifying assumption from a panel regression into a single time series moment by defining the cross-area average μ_t. Borusyak, Hull, and Jaravel (2018) defend the validity of shift-share instruments when the shifter is exogenous, a seemingly natural assumption in our setting given that stock market returns are nearly i.i.d. Nonetheless, since stock market returns are equilibrium outcomes (as most shifters are), identification of β_h also requires that other aggregate variables correlated with $R^m_{t-1,t}$ and not controlled for in X impact areas with high and low stock market wealth uniformly. Importantly, we do *not* require that stock market wealth be distributed randomly, and show in online Appendix Table A.5 that $S_{a,t}$ correlates with the share of a county's population with a college education and the median age, among other variables. Instead, as illustrated by equation (2), we require that high and low wealth areas not be heterogeneously affected by other aggregate variables that co-move with stock returns. This insight motivates our baseline specification and robustness analysis.

B. *Baseline Specification*

Our baseline specification implements equation (1) at the county level and at quarterly frequency, with outcome y either log employment or log quarterly payroll. We include the following controls in $X_{a,t-1}$: a county fixed effect, a state $\times$ quarter fixed effect, and eight lags of the "shock" variable $\{S_{a,t-j-1} R_{a,t-j-1,t-j}\}_{j=1}^{8}$. We also include interactions of $S_{a,t-1}$ with changes in other forms of aggregate wealth: the holding return on a 5-year Treasury bond, the log growth of national house prices between $t-1$ and t, and the log change in national labor income and noncorporate business income from $t-1$ to the cumulative total over the next 12 quarters (to capture human capital and private business wealth).[14] Finally, we also include a Bartik

[13] To derive this condition, let $\mathbf{Y}$ denote the $AT \times 1$ vector of $\Delta_{a,t-1,t+h} y$ stacked over A areas and T time periods, $\mathbf{S}$ the $AT \times T$ matrix containing the vector $(b_{1,t} S_{1,t-1} \cdots b_{A,t} S_{A,t-1})'$ in rows $A(t-1)+1$ to At of column t and zeros elsewhere, $\mathbf{R}$ the $T \times 1$ vector of stock market returns, $\mathbf{X}$ the $AT \times K$ matrix of K covariates stacked over areas and time periods, and $\boldsymbol{\epsilon}$ the $AT \times 1$ stacked vector of $\epsilon_{a,t-1,t+h}$. Then we can rewrite equation (1) in matrix form as $\mathbf{Y} = \beta_h \mathbf{SR} + \mathbf{X}\Gamma_h + \boldsymbol{\epsilon}$. It follows that $plim\,\hat{\beta}_h = \beta_h$ if $0 = \lim_{A,T\to\infty} (\mathbf{SR})'\boldsymbol{\epsilon} = \lim_{A,T\to\infty} \mathbf{R}'\mathbf{S}'\boldsymbol{\epsilon} = \lim_{A,T\to\infty} \sum_t R_{t-1,t} \sum_a b_{a,t} S_{a,t-1} \epsilon_{a,t-1,t+h} = E[R_{t-1,t} \mu_t]$.

[14] Specifically, we interact $S_{a,t-1}$ with (i) the holding return on a 5-year zero coupon Treasury bond using the updated Gürkaynak, Sack, and Wright (2006) dataset, (ii) the log change in the Case-Shiller national house price series, and (iii, iv) $\ln(\sum_{j=0}^{11} \mathcal{R}^{-j} A_{t+j}) - \ln A_{t-1}$ for A_t the aggregate labor compensation (NIPA code A4002C) or aggregate noncorporate business income (nonfarm sole proprietor income and partnership income, NIPA code A041RC) and a quarterly discount factor $\mathcal{R} = 1.03^{1/4}$. To see the rationale for the last two controls, let $H_t^{\infty} = \sum_{j=0}^{T} \mathcal{R}^{-j} A_{t+j}$ denote the discounted stream of labor (or private business) income A_t. The revision to human capital (or private

(1991) shift-share measure of predicted employment growth at horizon h based only on industry composition, $\Delta_{a,t-1,t+h} e^B$.[15] We weight regressions by 2010 population and report standard errors two-way clustered by time and county. Clustering by county accounts for any residual serial correlation in stock market returns and has a small effect on the standard errors in practice. Clustering by time allows for areas with high or low stock market wealth to experience other common shocks and accords with the recommendation of Adão, Kolesár and Morales (2019) in the special case of a single national shifter. Finally, we exclude from our baseline sample counties in the top 5 percent of the share of employees working at large (500+) firms, as these firms can have direct exposure to the stock market.[16]

C. *Threats to Identification and Motivation for Covariates*

Our identifying assumption is that following a positive stock return, areas with high stock market wealth relative to labor income do not experience unusually rapid employment or payroll growth—relative to their own mean and to other counties in the same state, and conditional on the included covariates—for reasons other than the wealth effect on local consumption expenditure. As emphasized by Goldsmith-Pinkham, Sorkin, and Swift (2018), this requirement mirrors the parallel trends assumption in a continuous difference-in-difference design with multiple treatments. Two main threats to identification exist.

The first threat occurs because stock prices are forward-looking, so fluctuations in the stock market may reflect news about deeper economic forces such as productivity growth that independently affect consumption and investment. This "leading indicator" channel confounds interpretation of the relationship between consumption and the stock market in aggregate time series data. Our cross-sectional research design requires only the weaker condition that areas with high and low stock wealth to labor income ratios not load differently on other aggregate variables that co-move with the stock market. Conceptually, such differential loading could occur if stock wealth correlates with other forms of wealth and the return on the stock market correlates with the returns on other forms of wealth. Inclusion in $X_{a,t-1}$ of interactions of $S_{a,t-1}$ with other aggregate variables directly addresses the possible heterogeneity in exposure to changes in four other types of wealth: human capital wealth, noncorporate business wealth, fixed income wealth, and housing wealth.[17] For

business) wealth in period t is $\left(E_t[H_t^\infty] - E_{t-1}[H_t^\infty]\right)/E_{t-1}[H_t^\infty] \simeq \ln E_t[H_t^\infty] - \ln E_{t-1}[H_t^\infty]$. Relative to this definition, our control (i) truncates the horizon at $T = 11$ (truncating at longer horizons gives similar results); (ii) replaces $E_t[H_t^{11}]$ with its perfect-forecast counterpart H_t^{11} (under rational expectations, this provides an unbiased measure of expected wealth); and (iii) replaces $E_{t-1}[H_t^{11}]$ with income in the last period, A_{t-1}. Under the efficient market hypothesis, this last step does not matter because both $E_{t-1}[H_t^\infty]$ and A_{t-1} are determined in period $t-1$ and therefore should be orthogonal to the stock return $R_{t-1,t}^m$.

15 The Bartik (1991) industry shift-share predicted employment growth between $t-1$ and $t+h$ is defined as $\Delta_{a,t-1,t+h} e^B = \sum_{i \in NAICS3} (E_{a,i,t-1}/E_{a,t-1})((E_{i,t+h} - E_{i,t-1})/E_{i,t-1})$, where $E_{a,i,t}$ denotes the (seasonally unadjusted) level of employment in NAICS 3-digit industry i in county a and period t, $E_{a,t}$ is total employment in county a, and $E_{i,t}$ is seasonally adjusted total national employment in industry i.

16 Data on payroll by firm size come from the Census Bureau's Quarterly Work Force Indicators. Because this dataset has less historical coverage than our baseline sample, we use the time series mean share for each county. This step contains little loss of information because the large payroll share is extremely persistent at the county level, with an R^2 of 0.85 from a regression of the quarterly share on county fixed effects.

17 For noncorporate business wealth, fixed income wealth, and housing wealth, we could alternatively try to control directly for changes in the local values of these variables. This alternative has two deficiencies. First, these

example, controlling for the interaction of $S_{a,t-1}$ and aggregate earnings addresses the possibility of high wealth areas having different exposure to aggregate earnings risk. Similarly, the Bartik variable controls for the possibility of high wealth counties concentrating in industries with higher stock market betas than those in low wealth counties or in industries that drive overall market returns, and the state-quarter fixed effects control non-parametrically for aggregate shocks that have heterogeneous impacts on different states. Finally, inclusion of the lags of $S_{a,t-1}R_{t-1,t}$ controls for the small serial correlation in stock returns shown in Figure 1, panel A.

The second threat to identification concerns the separation of a consumption wealth effect from firm investment or hiring responding directly to the change in the cost of equity financing. Indeed, the response of total national employment to an increase in the stock market cannot separately identify these two channels. Our local labor market analysis absorbs changes in the cost of issuing equity common across areas into the time fixed effect. Nonetheless, firms in high stock wealth areas may have a cost of capital more sensitive to the value of the stock market. Two aspects of our research design make such a correlation an unlikely driver of our results: (i) we find an employment response in nontradable but not in tradable industries, so differential access to capital markets would have to occur within areas and align with the tradable/nontradable sectoral distinction, and (ii) our baseline sample excludes counties in the top 5 percent of the share of employees working at large (500+) employee firms that might have greater access to public capital markets.

III. Results

A. *Baseline Results*

In this section we report our baseline results: (i) an increase in the stock market causes faster employment and payroll growth in counties with higher stock market wealth, (ii) the response is pronounced in industries that produce nontradable goods and in residential construction, and (iii) there is no increase in employment in industries that mostly produce tradable goods.

Figure 2 reports the time paths of responses of quarterly employment and payroll to an increase in stock market wealth; formally, the coefficients $\hat{\beta}_h$ from estimating equation (1). Table 1 reports the corresponding coefficients and standard errors for $h = 7$, where the stock market return occurs in period 0. Because the

variables may endogenously respond to local stock market wealth, making them an over-control. Second, measuring local business wealth and fixed income wealth poses a more formidable challenge than measuring local stock market wealth, because of the much larger variation in capitalization factors for the income streams generated by these variables and the particular sensitivity of fixed income wealth to the capitalization factor at interest rates near zero (Kopczuk 2015; Smith, Zidar, and Zwick, in progress). While this difficulty precludes estimation of the local labor market effects of changes in these other types of wealth, including interactions with the aggregate values of other wealth is still sufficient for identifying the stock market wealth effect. The reason is that heterogeneity in holdings of other wealth matters for our purpose only insofar as returns on such wealth correlate with our main regressor. Formally, denoting by $S^o_{a,t-1}R^o_{t-1,t}$ the change in some other type of wealth o, we can write $S^o_{a,t-1}R^o_{t-1,t} = \gamma S_{a,t-1}R^o_{t-1,t} + S^{o,\perp}_{a,t-1}R^o_{t-1,t}$, where $\gamma S_{a,t-1}$ is the fitted value from a regression of $S^o_{a,t-1}$ on $S_{a,t-1}$ and so by construction $S^{o,\perp}_{a,t-1}$ is orthogonal to $S_{a,t-1}$. Therefore, omitting the part $S^{o,\perp}_{a,t-1}R^o_{t-1,t}$ from the change in wealth of type o has no impact on the remaining variables in the regression (and note that we do not need to separately identify the parameter γ). As an example, interacting the Treasury return with stock wealth directly amounts to allowing for an arbitrary correlation between the levels of stock wealth and fixed income wealth across counties.

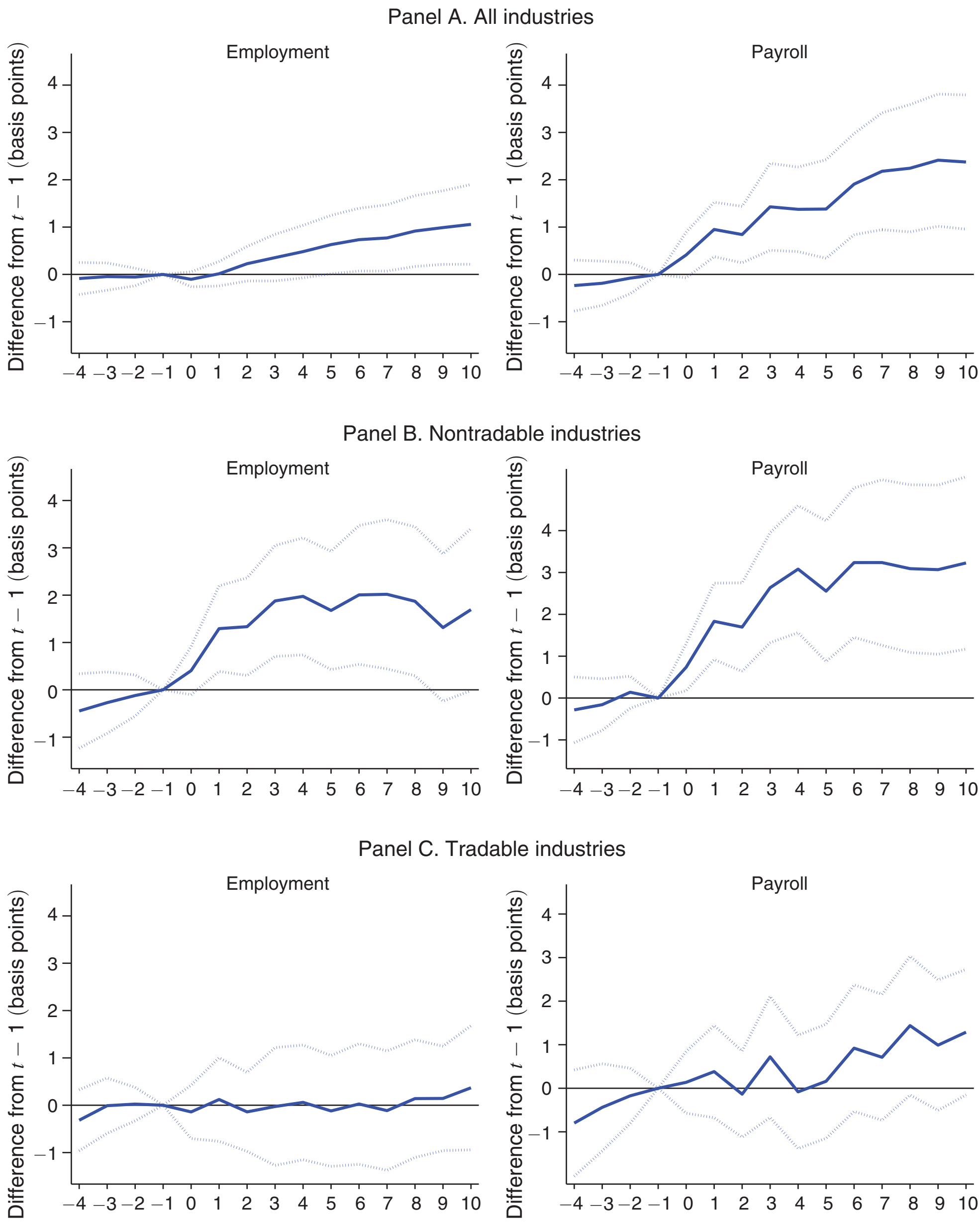

Figure 2. Baseline Results

Notes: The figure reports the coefficients β_h from estimating equation (1) for quarterly employment (left panels) and wages (right panels) at each quarterly horizon h shown on the lower axis. Panel A includes all covered employment and payroll; panel B includes employment and payroll in NAICS 44–45 (retail trade) and 72 (accommodation and food services); panel C includes employment and payroll in NAICS 11 (agriculture, forestry, fishing and hunting), NAICS 21 (mining, quarrying, and oil and gas extraction), and NAICS 31–33 (manufacturing). The shock occurs in period 0 and is an increase in stock market wealth equivalent to 1 percent of annual labor income. The dotted lines show the 95 percent confidence bands based on standard errors two-way clustered by county and quarter.

stock market is close to a random walk (Figure 1, panel B), these time paths should be interpreted as the dynamic responses to a permanent change in stock market

TABLE 1—BASELINE RESULTS

Sector:	All		Non-traded		Traded	
Dependent variable:	Emp. (1)	W&S (2)	Emp. (3)	W&S (4)	Emp. (5)	W&S (6)
Right hand side variables:						
$S_{a,t-1}R_{a,t-1,t}$	0.77	2.18	2.02	3.24	−0.11	0.71
	(0.36)	(0.63)	(0.80)	(1.01)	(0.64)	(0.74)
Horizon h	Q7	Q7	Q7	Q7	Q7	Q7
Population weighted	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State × time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Shock lags	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.66	0.64	0.39	0.48	0.35	0.36
Counties	2,901	2,901	2,896	2,896	2,877	2,877
Periods	92	92	92	92	92	92
Observations	265,837	265,837	263,210	263,210	252,928	252,928

Notes: The table reports coefficients and standard errors from estimating equation (1) for $h = 7$. Columns 1 and 2 include all covered employment and payroll; columns 3 and 4 include employment and payroll in NAICS 44-45 (retail trade) and 72 (accommodation and food services); columns 5 and 6 include employment and payroll in NAICS 11 (agriculture, forestry, fishing and hunting), NAICS 21 (mining, quarrying, and oil and gas extraction), and NAICS 31–33 (manufacturing). The shock occurs in period 0 and is an increase in stock market wealth equivalent to 1 percent of annual labor income. All columns also include eight lags $\{S_{a,t-j-1}R_{a,t-j-1,t-j}\}_{j=1}^{8}$, interactions of $S_{a,t-1}$ with the log change in national labor income and with non-corporate business income from $t-1$ to the cumulative total over the next 12 quarters, the interaction of $S_{a,t-1}$ and the holding return on a 5-year Treasury bond, the interaction of $S_{a,t-1}$ and the log growth of national house prices between $t-1$ and t, and a Bartik (1991) shift-share measure of predicted employment growth. For readability, the table reports coefficients in basis points. Standard errors in parentheses and double-clustered by county and quarter.

wealth. Panel A of Figure 2 shows no pre-trends in either total employment or payroll, consistent with the parallel trends assumption. Both series start increasing in period 1. Payroll responds more than employment, reflecting either rising hours per employee or rising compensation per hour. The point estimates indicate that a rise in stock market wealth in quarter t equivalent to 1 percent of labor income increases employment by 0.0077 log points (i.e., an approximately 0.77 basis point increase) and payroll by 0.0218 log points in quarter $t + 7$. The increases appear persistent.

Panels B and C examine the responses in industries classified as producing nontradable or tradable output, respectively. Employment and payroll in nontradable industries rise by more than the total effect. In contrast, the responses in tradable industries are flat following a positive stock market return. The horizon 7 differences between the tradable and nontradable employment and payroll coefficients are both significant at the 1 percent level. These patterns accord with the predictions of the theoretical model presented in the next section. They also militate against a leading indicator or cost-of-capital explanation since such confounding forces would have to apply only to the nontradable sector.

Figure 3 shows a large response of employment and payroll in the residential building construction sector (NAICS 2361). We show this sector separately because, while it also produces output consumed locally, the magnitude does not easily translate into our theoretical model since the sector produces a capital good (housing) that provides a service flow over many years. Thus, a desire by local residents to increase their consumption of housing services following a positive wealth shock will result

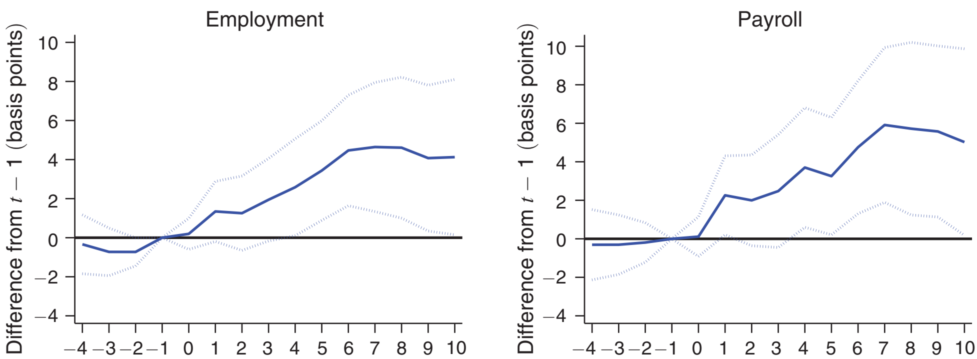

Figure 3. Response of Residential Construction

Notes: The figure reports the coefficients β_h from estimating equation (1) for residential building construction (NAICS 2361) employment and payroll at each quarterly horizon h shown on the lower axis. The shock occurs in period 0 and is an increase in stock market wealth equivalent to 1 percent of annual labor income. The dotted lines show the 95 percent confidence interval bands.

in a front-loaded response of employment in the construction sector. Nonetheless, the large response of residential construction provides additional evidence of a local demand channel at work. We find no corresponding response in construction sectors unrelated to residential building.[18]

Figure 4 reports the responses of population and the employment-population ratio.[19] The response of population lies well below the response of total employment and the data cannot reject no population response at the horizon we examine. As a result, the employment-population-ratio closely tracks the response of total employment.

B. *Robustness*

Tables 2 and 3 report results from a number of robustness exercises for the horizon $h = 7$ overall, nontradable, and tradable responses of employment and payroll. The first row of each table reproduces the baseline specification.

Table 2 shows robustness to the covariates included in the baseline specification. Row 2 expands the variation used to identify the response by removing the interactions of $S_{a,t-1}$ with changes in aggregate labor income, noncorporate income, bond wealth, and house prices, and the Bartik control. The results are similar to the baseline specification. The insensitivity reflects a combination of two forces: (i) the loadings on the other aggregate variables do not vary too much with stock wealth, and (ii) as illustrated in Figure 1, panel C, while stock prices are not

[18] In unreported results, we find smaller but statistically significant positive responses in specialty trade contractors (NAICS 238), a category that includes a number of sectors (electrical contractors, plumbers, etc.) involved in the construction of residential buildings. In sharp contrast, there is a flat or slightly negative response in heavy and civil engineering construction (NAICS 237). We also find a large and statistically significant response of new building permits using the Census Bureau residential building permits survey.

[19] The Census Bureau reports population by county for July 1 of each year. We linearly interpolate these data to obtain a quarterly series. We construct the employment-population ratio by dividing the employment measure previously described by this population series.

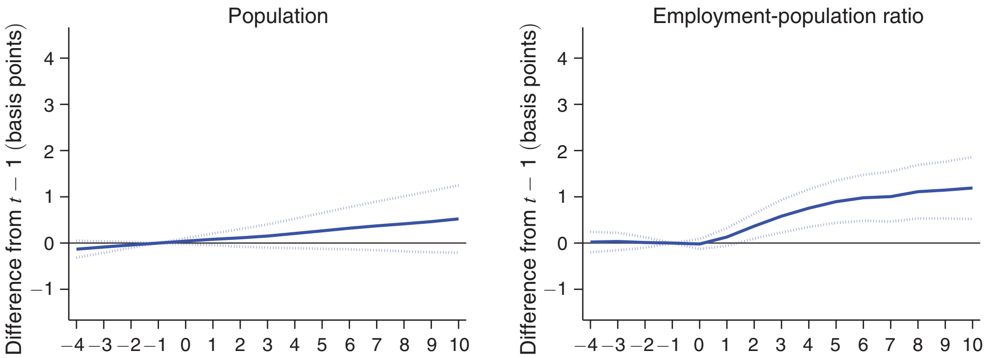

FIGURE 4. RESPONSE OF POPULATION AND EMPLOYMENT-POPULATION RATIO

Notes: The figure reports the coefficients β_h from estimating equation (1) for total county population (left panel) and the ratio of employment to county population (right panel) at each quarterly horizon h shown on the lower axis. The shock occurs in period 0 and is an increase in stock market wealth equivalent to 1 percent of annual labor income. The dashed lines show the 95 percent confidence interval bands.

TABLE 2—ROBUSTNESS TO COVARIATES

	Total		Nontradable		Tradable	
Dependent variable:	Emp.	Payroll	Emp.	Payroll	Emp.	Payroll
Specification						
1. Baseline	0.77	2.18	2.02	3.24	−0.11	0.71
	(0.36)	(0.63)	(0.80)	(1.01)	(0.64)	(0.74)
2. Only county, state × quarter fixed effects	1.04	2.82	1.21	2.92	0.02	1.55
	(0.40)	(0.74)	(1.06)	(1.06)	(0.87)	(1.04)
3. Control high earners	0.59	1.65	1.90	2.83	−0.06	0.30
	(0.35)	(0.58)	(0.81)	(0.94)	(0.65)	(0.70)
4. Aggregate TFP sensitivity	0.66	2.06	1.84	3.02	−0.11	0.74
	(0.31)	(0.62)	(0.76)	(0.95)	(0.58)	(0.71)
5. Control local house prices	0.70	2.15	1.50	2.82	−0.45	0.35
	(0.37)	(0.65)	(0.64)	(0.92)	(0.62)	(0.70)
6. Control large firm share	0.70	2.05	1.93	3.10	−0.17	0.67
	(0.34)	(0.59)	(0.76)	(0.96)	(0.61)	(0.71)
7. Control lagged outcomes	0.75	2.17	2.10	3.19	−0.19	0.75
	(0.35)	(0.62)	(0.81)	(0.99)	(0.70)	(0.74)
8. Commuting zone × time fixed effects	1.09	2.24	2.41	3.69	−0.37	0.24
	(0.38)	(0.67)	(0.96)	(1.11)	(0.64)	(0.86)

Notes: The table reports alternative specifications to the baseline for $h = 7$. The shock occurs in period 0. Each cell reports the coefficient and standard error from a separate regression with the dependent variable indicated in the table header and the specification described in the left-most column. For readability, the table reports coefficients in basis points. Standard errors in parentheses and double-clustered by county and quarter.

strictly exogenous, much of the volatility in the stock market and hence the variation in our main regressor occurs for reasons unrelated to other aggregate variables.

The remaining rows add additional control variables to the baseline specification to address particular concerns. While our baseline specification already includes a linear interaction of stock wealth/income and aggregate labor earnings, previous work has found especially high sensitivity among very high earners (Guvenen, Ozkan and Song 2014). To address this concern, row 3 includes an indicator for

Table 3—Other Robustness

Dependent variable:	Total Emp.	Total Payroll	Nontradable Emp.	Nontradable Payroll	Tradable Emp.	Tradable Payroll
Specification						
1. Baseline	0.77	2.18	2.02	3.24	−0.11	0.71
	(0.36)	(0.63)	(0.80)	(1.01)	(0.64)	(0.74)
2. Keep if $R_{t-1,t} \in [\mathrm{P5}, \mathrm{P95}]$	1.15	2.98	3.54	5.14	0.30	1.87
	(0.46)	(0.93)	(1.01)	(1.25)	(0.97)	(1.24)
3. Trim top/bottom 1 percent of $S_{a,t}$	1.03	2.93	2.65	4.56	0.53	1.34
	(0.51)	(0.91)	(1.15)	(1.40)	(1.06)	(1.11)
4. Drop S&P 500 HQs	0.30	0.69	1.68	1.98	0.03	0.72
	(0.21)	(0.39)	(0.67)	(0.68)	(0.81)	(0.88)
5. Drop Forbes Top Private HQs	0.40	0.89	1.88	2.66	0.29	0.75
	(0.25)	(0.42)	(0.76)	(0.84)	(0.78)	(0.85)
6. Unweighted	0.48	0.85	2.97	2.86	0.10	0.55
	(0.31)	(0.42)	(1.20)	(1.03)	(0.84)	(1.05)
7. Trim by population	0.83	1.84	2.15	3.04	0.52	1.52
	(0.31)	(0.56)	(0.79)	(0.91)	(0.74)	(0.94)
8. Price component only	0.67	2.05	1.80	2.94	−0.12	0.74
	(0.35)	(0.61)	(0.78)	(0.98)	(0.59)	(0.71)
9. IV with lagged wealth	0.75	1.91	1.61	2.61	−0.22	0.43
	(0.37)	(0.60)	(0.77)	(0.96)	(0.57)	(0.72)
10. IV with fixed dividends/income	0.88	2.60	1.64	2.90	0.23	1.21
	(0.12)	(0.18)	(0.21)	(0.25)	(0.42)	(0.51)
11. Concentration-based T/NT	0.77	2.18	2.13	4.26	−0.72	0.62
	(0.36)	(0.63)	(0.62)	(1.00)	(0.98)	(1.61)
12. Across CBSAs	0.44	1.80	2.56	3.00	0.68	1.95
	(0.47)	(1.03)	(1.53)	(1.63)	(1.61)	(1.73)

Notes: The table reports alternative specifications to the baseline for $h = 7$. The shock occurs in period 0. Each cell reports the coefficient and standard error from a separate regression with the dependent variable indicated in the table header and the specification described in the left-most column. For readability, the table reports coefficients in basis points. Standard errors in parentheses and double-clustered by county and quarter.

being in the top 5 percent of counties by share of returns with greater than \$200,000 in adjusted gross income, interacted with time fixed effects. This row illustrates that controlling flexibly for cyclical patterns of counties with a large share of high earners has a small impact on the coefficients. Motivated by theories of news-driven business cycles (Beaudry and Portier 2006), row 4 adds an interaction of $S_{a,t-1}$ with the Fernald (2012b) measure of TFP growth between $t-1$ and $t+7$, again with little effect. Row 5 adds contemporaneous and 12 lags of local house prices. While our baseline specification controls for the sensitivity of wealthier areas to the aggregate housing cycle, adding the local controls allows this sensitivity to vary with the performance of the stock market.[20] Row 6 controls for the share of payroll in a county at establishments belonging to large (500+ employee) firms interacted with the stock market return. Large firms are more likely to have publicly traded equity and thus experience a direct reduction in their cost of capital when the stock market

[20] We use the Federal Housing Finance Agency (FHFA) annual county-level repeat sales house price index and interpolate to obtain a quarterly series. In unreported results, we also find the response of residential construction remains quantitatively robust to controlling for contemporaneous and lags of house price growth so that the construction response does not merely reflect a run-up in local house prices in high wealth areas before the stock market rises.

rises; the stability of coefficients indicates that our results do not reflect an investment response by such firms. Row 7 includes lagged outcomes to control directly for any pre-trends.[21] Row 8 replaces the state-by-quarter fixed effects with commuting zone-by-quarter fixed effects. In this specification, identification comes from comparing the responses of high and low wealth counties within the same commuting zone. Adding these controls has a minor effect on the point estimates.

Table 3 collects other robustness exercises. Rows 2 and 3 show that the quarters with the most extreme stock returns and the counties with the largest and smallest values of $S_{a,t}$ do not drive the results, although excluding these quarters and counties increases the standard errors. Row 4 excludes counties in which at least one S&P 500 constituent firm has its headquarters, while row 4 excludes counties headquartering a firm on the Forbes list of the largest private companies. The coefficients remain qualitatively similar, although the payroll responses drop somewhat when excluding S&P 500 headquarter counties. We suggest caution in interpreting these results, however, because these 130 counties account for more than half of total stock wealth and payroll, so that excluding them substantially alters the characteristics of the sample. Rows 5 and 6 show robustness to not weighting the regressions and to trimming at the first and ninety-ninth percentile of county population.

The next three rows alter the shock variable. Row 8 uses only the price component of the S&P 500 return with similar results. Row 9 instruments $S_{a,t-1}R_{a,t-1,t}$ with $S_{a,t-8}R_{a,t-1,t}$ and row 10 uses the within-county mean ratio of dividend income to labor income interacted with the time-varying price-dividend ratio and return as an instrument. Because the dividend-labor income ratio changes little over time, instrumenting with the lagged wealth variable or fixing this ratio has a small effect on the results.

Row 11 uses an alternative classification of industries into tradable and nontradable, based on their geographic concentration. Intuitively, if locations all have similar preferences, then industries with concentrated production must sell to buyers in other regions. This idea traces back at least to Krugman (1991, p. 55) and has been pursued in Ellison and Glaeser (1997), Jensen and Kletzer (2005), and Mian and Sufi (2014), among others. We follow these authors and define a tradability index for industry i as $G_i = \sum_a (s_{a,i} - x_a)^2$, where $s_{a,i}$ denotes the share of employment in industry i located in county a and x_a denotes the share of total employment located in county a, and classify industries in the bottom quartile of this index as nontradable and industries in the top quartile as tradable. We obtain responses very similar to those using our baseline categorization.[22]

[21] We include both a county fixed effect and lags of the dependent variable because of the large time dimension (roughly 100 quarters) of the data (Alvarez and Arellano 2003).

[22] We construct the index at the NAICS 3 digit level and group industries, such that the share of total employment in each quartile is the same. The classification has substantial overlap with our baseline categorization: 7 of the 12 least-concentrated industries are in NAICS 44–45 or 72, and 27 of the 45 most-concentrated industries are in NAICS 11, 21, or 31–33 (the concentrated industries are smaller on average). Even at the 3 digit level, disclosure limitations affect the number of industries reporting employment and payroll in each period. We restrict to county-quarters with the same number of industries reporting non-missing employment and wages in periods $t-1$ and $t+7$, resulting in a final sample about one-half as large as our baseline and explaining why we prefer the simpler 2 digit-based classification for our baseline.

The last row returns to the baseline specification but expands the geographic unit to a Core Based Statistical Area (CBSA).[23] The point estimates change little except in the tradable sector where they rise slightly, while the standard errors increase substantially. The larger standard errors reflect the decrease in wealth variation after averaging across counties within a CBSA and the smaller sample size. The larger coefficients in the tradable sector could reflect spending on tradable goods produced outside of a resident's county but within the CBSA; however, the data do not reject equality of the coefficients in the county and CBSA specifications.

C. *Decomposing Variation*

In this section we provide evidence on whether certain areas "drive" the results in the sense of Andrews, Gentzkow, and Shapiro (2017). Consider the specification reported in row 2 of Table 2 in which $X_{a,t}$ includes only a county fixed effect and state-by-quarter fixed effect. In this case, letting $\tilde{z}_{a,t}$ denote $S_{a,t-1} R_{t-1,t}$ demeaned by county and state-by-quarter, $\Delta_{a,t}\tilde{y}$ the outcome after demeaning with respect to county and state-by-quarter (where for notational simplicity we have suppressed the dependence of Δ on the horizon h), π_a the 2010 population in county a, and s index states, we can decompose the OLS coefficient as follows:

$$\beta = \sum_s w_s \beta_s,$$

where

$$\beta_s \equiv \left(\sum_{a \in s} \sum_t \pi_a \tilde{z}_{a,t}^2\right)^{-1} \sum_{a \in s} \sum_t \pi_a \tilde{z}_{a,t} \Delta_{a,t}\tilde{y},$$

$$w_s \equiv \left(\sum_{a'} \sum_t \pi_{a'} \tilde{z}_{a',t}^2\right)^{-1} \left(\sum_{a \in s} \sum_t \pi_a \tilde{z}_{a,t}^2\right).$$

Here, β_s is the regression coefficient obtained by using only observations from state s and the weight w_s is the contribution to the total (residual) variation in the regressor from state s.[24] The weights $\{w_s\}$ are all positive and sum to one.

Table 4 reports the ten states with the largest weight in the regression. Not surprisingly, since the regression weights by population, California, Texas, and Florida rank among the states with the highest weights. More surprisingly, Florida, with 6 percent of the 2010 population, has a weight in the regression above 30 percent. This high share reflects the large variation across Florida counties in stock market

[23] The Office of Management and Budget (OMB) defines CBSAs as areas "containing a large population nucleus and adjacent communities that have a high degree of integration with that nucleus" and has designated 917 CBSAs of which 381 (covering 1,166 counties) are Metropolitan Statistical Areas (MSAs) and the remainder (covering 641 counties) are Micropolitan Statistical Areas (MiSAs). An MSA is a CBSA with an urban core of at least 50,000 people. The remaining counties not affiliated with a CBSA are rural. Because CBSAs may contain counties from multiple states (e.g., the Boston-Cambridge-Newton MSA contains five counties in MA and two counties in NH), the specification in this row replaces the state $\times$ quarter fixed effects with quarter fixed effects.

[24] We could have done this decomposition for the baseline specification after partialing out the interactions of $S_{a,t-1}$ with other aggregate variables and the Bartik employment variable. In that case, the coefficient β_s would no longer equate to the coefficient from estimating the regression in state s only because the coefficient on these additional controls would differ across states. The alternative of re-estimating the baseline specification while dropping one state at a time yields conclusions similar to those obtained from Table 4.

Table 4—Ten States with Largest Weight

State	Population share	Weight	β_s, nontradable wage bill
Florida	0.061	0.313	0.30
California	0.121	0.081	5.01
Virginia	0.026	0.050	2.36
Texas	0.081	0.039	1.98
Ohio	0.037	0.034	1.90
North Carolina	0.031	0.032	3.14
Missouri	0.019	0.031	3.23
Illinois	0.042	0.027	7.88
Washington	0.022	0.027	8.46
Maryland	0.019	0.026	5.46

wealth. On the other hand, Florida does *not* drive the finding of a positive regression coefficient, as the Florida-only nontradable labor bill coefficient is *smaller* than the overall coefficient. Hence excluding Florida from the sample would *raise* the estimated coefficient. Virginia also receives a larger weight in the regression than its population share, reflecting the contrast in the state between wealthier northern suburbs of Washington, DC and poorer southern counties. Notably, all 10 of the states with the largest weight have $\beta_s > 0$. Thus, no one or two states drive the overall result.

D. *Heterogeneity*

This section considers heterogeneity in the labor market response. Figure 5 reports results for the coefficients on nontradable payroll, the variable most directly used in our theoretical analysis, from augmenting equation (1) by replacing $\beta_h[S_{a,t-1} R_{a,t-1,t}]$ with $\sum_{m=1}^{M} \beta_h^m \times \mathbf{1}\{o_{a,t} \in m\} \times [S_{a,t-1} R_{a,t-1,t}]$, where $\mathbf{1}\{o_{a,t} \in m\}$ is an indicator for observation $o_{a,t}$ belonging to set m. The dimensions of heterogeneity considered are whether the stock return is positive or negative, the sample period, and wealth level.

The left bars show a similar response of nontradable payroll to a negative or positive stock return. Nearly 75 percent of quarters in our sample contain a positive return, explaining the higher precision around the coefficient on positive returns. The middle bars show the response split before and after the end of the NASDAQ bust. The response is slightly larger in the more recent period, but not statistically significantly different.[25]

Many theories of consumption predict higher MPCs for less wealthy households. In the context of stock market wealth, Di Maggio, Kermani, and Majlesi (2020) find a higher MPC in Sweden among households in the lower half of the wealth distribution. In our regional context, such heterogeneity could also arise from local general equilibrium amplification declining in wealth (since, all else equal, a smaller MPC

[25] Not shown, this pattern holds across other outcomes except total employment, which responds much more strongly in the latter period. Our theory can rationalize a larger response of employment if the more recent period featured greater wage rigidity.

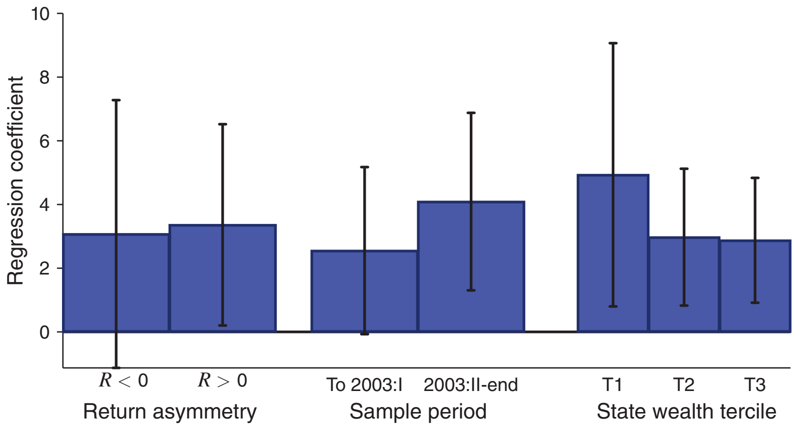

Figure 5. Heterogeneity

Notes: The figure reports the coefficients β_h^m from estimating equation (1) for the nontradable wage bill at horizon $h = 7$, where m indexes positive versus negative stock return (left bars), before or after 2003:II (middle bars), or tercile of the state's per capita wealth distribution (right bars). The whiskers show the 95 percent confidence intervals.

also leads to a smaller multiplier effect). The right bars show that the coefficient indeed declines in tercile of state wealth, although the differences are not statistically significant.[26]

The possibility of heterogeneous MPCs also has implications for the interpretation of our baseline coefficients. In general, when treatment effects are correlated with the regressor, the OLS coefficient in a specification without treatment effect heterogeneity need not lie in the convex hull of the individual treatment effects; intuitively, if low wealth areas have high MPCs and high wealth areas have low MPCs, an increase in the stock market could induce the same change in spending in both low and high wealth areas. However, an advantage of a regional approach is that it already reflects the wealth-weighted average MPC in a region. Because stock wealth heterogeneity is substantially greater within than across counties, this means that the cross-county regression approximately reflects the wealth-weighted average MPC across *all* stockholders—the MPC that matters for *aggregate* stock wealth fluctuations. Online Appendix A.5 establishes this claim quantitatively in Monte Carlo exercises on simulated data that match the empirical distributions of stock market participation in each county, stock wealth-by-income of stockholders, and the cross-county distribution of average stock wealth. We first show that with heterogeneity in the MPC of stockholders not correlated with stock wealth, our empirical design exactly reflects the true wealth-weighted MPC. Second, when

[26]We split states by tercile of their time-averaged real (deflated by the price index for personal consumption expenditure) dividends per capita. Splitting by state wealth level maintains the identification of each coefficient as coming only from within-state variation. The terciles are Alabama, Arkansas, Delaware, Georgia, Idaho, Indiana, Kentucky, Louisiana, Mississippi, New Mexico, North Carolina, North Dakota, Oklahoma, Tennessee, Texas, Utah, West Virginia (tercile 1); Alaska, Arizona, California, Hawaii, Iowa, Maine, Michigan, Montana, Nebraska, New York, Ohio, Oregon, Rhode Island, South Carolina, South Dakota, Wisconsin, Wyoming (tercile 2); Colorado, Connecticut, Florida, Illinois, Kansas, Maryland, Massachusetts, Minnesota, Missouri, Nevada, New Hampshire, New Jersey, Pennsylvania, Vermont, Virginia, Washington (tercile 3).

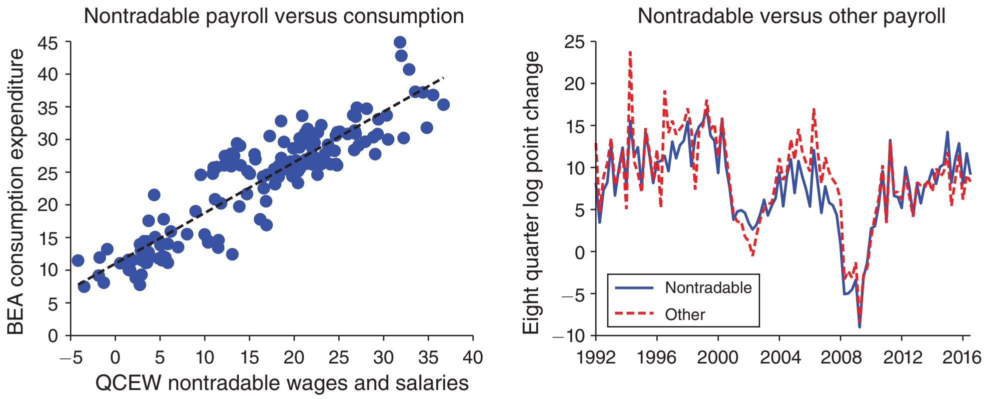

Figure 6. Nontradable Payroll, Consumption Expenditure, and Total Payroll

Notes: The left panel presents a scatter plot of five-year log changes in state-level QCEW nontradable wages and salaries and state-level BEA personal consumption expenditure, for each five-year period corresponding to processed quinquennial Economics Censuses (1997–2002, 2002–2007, 2007–2012). The right panel shows 8 quarter log changes in national QCEW wages and salaries in the nontradable sector (NAICS 44–45 and 72) and all other sectors.

the household-level MPC declines in stock wealth, our design understates the true wealth-weighted MPC, making our estimates if anything a lower bound. However, even for a strong negative relationship, the difference in coefficients is less than 10 percent.

E. *Labor Income versus Consumption Expenditure*

Our analysis so far has focused on the impact on labor market variables. Shortly, we will use economic theory to relate the response of payroll in the nontradable sector to the MPC out of stock market wealth. Before turning to that analysis, we establish in this section a tight empirical connection between labor market outcomes and consumption and present direct empirical evidence of a consumption expenditure response.

We first show that nontradable payroll growth (that we estimate) closely tracks consumption expenditure growth at the state level. The left panel of Figure 6 presents a scatter plot of five-year log changes in state-level QCEW nontradable wages and salaries and state-level BEA personal consumption expenditure (the lowest level of aggregation at which BEA reports consumption expenditure), for each five-year period corresponding to processed quinquennial Economics Censuses (1997–2002, 2002–2007, 2007–2012). We restrict attention to these five-year intervals in which consumption expenditure reflects actual sales data (Awuku-Budu et al. 2016). The two series exhibit a strong positive relationship.

Next, our theoretical analysis in Section 6 will require an assumption of homotheticity across nontradable and other sectors. The right panel of Figure 6 shows evidence of this relationship by plotting eight quarter log changes of national nontradable payroll and total payroll in all other sectors in the QCEW. At the local level, these two series exhibit different responses to increases in stock wealth, with nontradable payroll rising more sharply. At the national level these series co-move uniformly over time, with a regression coefficient of 0.96 (Newey-West standard

Table 5—Cross-State Expenditure Results

Coefficient	Conventional two-way clustered standard error	LZ2 two-way clustered standard error	BM degrees of freedom
4.82	1.97	2.85	4.50

Notes: The table reports results from estimating $\Delta_{a,t-1,t+h} y = \beta_h \left[S^C_{a,t-1} R_{a,t-1,t} \right] + \Gamma'_h X_{a,t-1} + \epsilon_{a,t-1,t+h}$, where y is total consumption expenditure in state a, $h = 2$ years, $S^C_{a,t-1}$ is the ratio of stock wealth to consumption expenditure in state a in period $t-1$, and the remaining variables are analogous to our baseline specification. The first column reports the regression coefficient. The second column reports the standard error clustered by state and year using the conventional degrees of freedom adjustment. Column 3 reports the standard error using the "LZ2" adjustment recommended by Imbens and Kolesár (2016) for samples with relatively few clusters. Column 4 reports the Imbens and Kolesár (2016) suggested degrees of freedom for the t-distribution implied by columns 1 and 3.

error 0.077) and R^2 of 0.79. The similarities in the mean growth rates and high frequency movements of these two series signify homotheticity across locally nontradable spending and other categories. We will use this property to infer the response of national spending from the response of local nontradable spending.

Online Appendix A.6 provides further evidence of preference homotheticity across nontradable and other sectors using the Consumer Expenditure Survey (CE). Online Appendix Table A.8 reports Engel curves for selected expenditure categories. Our theoretical analysis will not require homotheticity across all expenditure categories, and we confirm in online Appendix Table A.8 that our nontradable grouping includes both luxury (jewelry, restaurants) and necessity (food at home) items. However, the overall nontradable category of retail and restaurants moves close to proportionally with total expenditure across households. Online Appendix Table A.9 extends the Dynan and Maki (2001) analysis of securities-owning households in the CE to estimate the effect of the stock market separately for these households' retail expenditure and other expenditure. Again consistent with homotheticity holding for the broad category of retail and restaurants, we find similar total responses across the two types of expenditure.

Finally, we provide direct evidence of the response of consumption expenditure to stock wealth in Table 5, using the BEA state-level data. These data start in 1997 and have an annual frequency, resulting in a very large reduction in both the cross-section (roughly 3,000 counties to 50 states) and time (93 quarters to 18 years) dimensions relative to our baseline, county-quarter specification. Guided by the theoretical model in the next section, we also modify equation (1) by replacing $S_{a,t-1}$ with $S^C_{a,t-1}$, defined as the ratio of stock wealth to consumption expenditure in state a and year $t-1$.

We estimate a cross-state coefficient of 4.8. As we will see, this magnitude accords extremely well with the coefficient on nontradable payroll of 3.2 estimated in our baseline specification, providing additional support for the homotheticity assumption and the theoretical mapping of our baseline specification into the MPC out of stock wealth in the next section. From an econometric identification standpoint, this coincidence is remarkable, as our baseline specification uses only within-state variation while Table 5 uses only cross-state variation for identification. However, the coefficient is estimated less precisely than in our baseline, reflecting the large reduction in sample size. Moreover, since we have few clusters in the time dimension

(18 years), the conventional clustered standard errors reported in column 2 might be biased. We address this issue by reporting in column 3 the standard error using the "LZ2" bias-reduction adjustment recommended by Imbens and Kolesár (2016) for samples with relatively few clusters and in column 4 the Imbens and Kolesár (2016) suggested degrees of freedom for the t-distribution implied by columns 1 and 3.

IV. Theoretical Model

This section develops a stylized theoretical model to interpret the empirical analysis. We present the main equations and results in the main text and relegate additional details to online Appendix B. We use the model to illustrate the cross-sectional effects of changes in aggregate stock prices and to validate our empirical specification. In subsequent sections, we calibrate the model and structurally interpret our empirical findings.

We start with a brief overview of the model's ingredients and their role in our analysis. There is a continuum of areas denoted by subscript a; infinite number of periods denoted by subscript $t \in \{0,1,2,\ldots\}$; two factors of production, labor L and capital K; two goods denoted by superscripts $\{N,T\}$, nontradables and tradables; and two types of agents in each area denoted by superscript $i \in \{s,h\}$, "stockholders" and "hand-to-mouth" households.

Our focus is on period 0, which we interpret as the "short run" with the key feature that labor is specific to the area and nominal wages are (potentially) partially sticky. We assume (for now) that monetary policy stabilizes aggregate demand by stabilizing the average wage at a nominal target level. However, since areas are not symmetric, monetary policy does not stabilize demand in each area. Therefore, local labor market outcomes in period 0 are determined by local demand. In contrast, we interpret periods $t \geq 1$ as the "long run" in which labor is fully mobile and the macroeconomic outcomes in each area are determined solely by productivity. Capital is fully mobile across areas in all periods and has a single (aggregate) price, although this assumption is inessential to our analysis.

The aggregate price of capital in period 0 ("the stock market") is endogenous and can change due to fluctuations in its expected productivity in periods $t \geq 1$. Importantly, initial capital ownership ("stock wealth") is heterogeneous across areas. Our goal is to analyze how changes in the aggregate price of capital affect local labor market outcomes. The nontradable sector plays a central role in this analysis and in our calibration.

Finally, "stockholders" make endogenous consumption-savings and portfolio decisions and provide labor exogenously. "Hand-to-mouth" households spend their income in every period, while supplying labor endogenously (with partially sticky wages). These features isolate the stock wealth effect on consumption from wealth effects on labor supply and allow the model to generate empirically reasonable Keynesian multiplier effects and changes in labor.

A. *Environment and Equilibrium*

Each area contains a representative stock-holding household with relative mass $1-\theta$ and hand-to-mouth household with relative mass θ. In each period t

and area a, each household $i \in \{s,h\}$ divides its consumption $C^i_{a,t}$ between a nontradable good that must be consumed in the area where it is produced, $C^{i,N}_{a,t}$, and a tradable good that can be transported costlessly across areas, $C^{i,T}_{a,t}$, to maximize the consumption aggregator,

$$C^i_{a,t} = \left(C^{i,N}_{a,t}/\eta\right)^{\eta}\left(C^{i,T}_{a,t}/(1-\eta)\right)^{1-\eta}.$$

Here, η denotes the share of nontradables in consumption.

The nontradable good is produced by competitive firms using labor $L^N_{a,t}$ and capital $K^N_{a,t}$ and the Cobb-Douglas technology,

$$Y^N_{a,t} = \left(K^N_{a,t}/\alpha^N\right)^{\alpha^N}\left(L^N_{a,t}/(1-\alpha^N)\right)^{1-\alpha^N}.$$

Here, $1-\alpha^N$ denotes the share of labor in the nontradable sector. The tradable good can be produced by a technology that uses tradable inputs produced in each area using local labor $L^T_{a,t}$ and capital $K^T_{a,t}$ and the Cobb-Douglas technology,

$$Y^T_t = \left(\int_a \left(Y^T_{a,t}\right)^{\frac{\varepsilon-1}{\varepsilon}} da\right)^{\frac{\varepsilon}{\varepsilon-1}},$$

where

$$Y^T_{a,t} = \left(K^T_{a,t}/\alpha^T\right)^{\alpha^T}\left(L^T_{a,t}/(1-\alpha^T)\right)^{1-\alpha^T}.$$

The elasticity of substitution $\varepsilon > 0$ governs the effect of unit costs in an area on the exports from that area. The term $1-\alpha^T$ captures the share of labor in the tradable sector.

Starting from period 1 onward, the tradable good can also be produced with another technology that uses only capital,

$$\tilde{Y}^T_t = D^{1-\alpha^T}\tilde{K}^T_t \qquad \text{for } t \geq 1.$$

The (future) productivity parameter D determines the rental rate of capital in periods $t \geq 1$. This technology does not play an important role beyond the asset pricing side of the model. Specifically, we will obtain changes in stock prices in period 0 by varying the future productivity, D. The normalizing power $1-\alpha^T$ simplifies the expressions.[27]

Areas are identical except for their initial capital wealth. The representative stockholder in area a enters period 0 owning $(1+x_{a,0})/(1-\theta)$ units of capital, where $\int_a x_{a,0}\,da = 0$ (so that the area owns $1+x_{a,0}$ units of capital). We let Q_0 denote the (cum-dividend) price of capital at the beginning of period 0 and normalize the aggregate capital supply to one. Therefore, $(1+x_{a,0})\,Q_0$ denotes the value of capital and, hence, the stock market wealth held by all stockholders in area a at the

[27] We exclude this technology from period 0 (our focus) to ensure the production side is homothetic. This homotheticity simplifies the analysis and plays a role for some of our results (as we describe subsequently).

start of period 0. Consequently, the distribution of capital ownership, $\{x_{a,0}\}_a$, determines the cross-sectional heterogeneity of stock wealth.

Stockholders supply labor exogenously, $L_{a,t}^s = \bar{L}$ for each a, at the equilibrium wage denoted by $W_{a,t}$. They choose the paths of their consumption, $\{C_{a,t}^s\}_{t=0}^{\infty}$, and capital holdings, $\{(1 + x_{a,t})/(1 - \theta)\}_{t=1}^{\infty}$, (with their residual savings invested in the risk-free asset), to maximize a time-separable log utility function,

$$\sum_{t=0}^{\infty} (1 - \rho)^t \log C_{a,t}^s, \tag{3}$$

subject to standard budget constraints that we relegate to the online Appendix [cf. (B.9)]. Here, $1 - \rho \in (0,1)$ denotes the one-period discount factor. The elasticity of intertemporal substitution of one simplifies the analysis and is empirically plausible.

Hand-to-mouth households are myopic and spend their labor income in all periods, $P_{a,t} C_{a,t}^h = W_{a,t} L_{a,t}^h$, and do not hold any financial assets. We model their labor supply to incorporate both some degree of wage stickiness and disutility of labor. Specifically, the representative hand-to-mouth household in an area is subdivided into a continuum of worker types denoted by $\nu \in [0,1]$. A worker of type ν supplies specialized labor services $L_{a,t}^h(\nu)$ subject to a constant elasticity labor demand curve determined by the aggregate demand for labor in the area as well as the elasticity of substitution ε_w between specialized labor types. A fraction $1 - \lambda_w$ of the labor types (the sticky workers) supply labor at the preset wage $\bar{W}$, which is the average nominal wage level targeted by monetary policy (as we describe subsequently). The remainder (the flexible workers) set a wage $W_{a,t}^h(\nu)$ to maximize

$$C_{a,t}^h(\nu) - \chi \frac{\left(L_{a,t}^h(\nu)\right)^{1+\varphi^h}}{1 + \varphi^h},$$

where φ^h denotes the inverse of the Frisch elasticity of labor supply. Thus, the worker chooses labor according to Greenwood, Hercowitz, and Huffman (1988) preferences, which omit a wealth effect on labor supply.

Finally, the risk-free asset is in zero net supply. We denote the gross nominal risk-free interest rate between periods t and $t + 1$ with R_t^f. Monetary policy sets R_t^f to stabilize the average nominal wage at the target level,

$$\int_a W_{a,t} da = \bar{W} \qquad \text{for each } t.$$

When areas are symmetric, this policy ensures labor supply in each area is at its "frictionless" level: the level that obtains without nominal rigidities (since the sticky workers set wages equal to the policy target). With asymmetries across areas, the policy stabilizes the labor supply across areas "on average."[28] Online Appendix B.1 completes the description of the setup and defines the equilibrium.

Online Appendix B.2.2 characterizes the equilibrium in periods $t \geq 1$ in which labor (as well as capital) is mobile across areas. The economy immediately reaches

[28] To simplify the exposition, we do not explicitly model money or its liquidity services. These features can be added to the model without changing anything substantive (see Woodford 1998 for further discussion).

a steady state in which nominal wages are equal to the monetary policy target, $W_{a,t} = \bar{W}$, and the equilibrium interest rate and the price of capital are constant, $R_t^f = 1/(1-\rho)$ and $Q_t = \bar{W}D/\rho$ [cf. Proposition 1]. We next turn to our focus, period 0.

B. *Consumption Wealth Effect*

Online Appendix B.2.3 characterizes the equilibrium and establishes that aggregate consumption in the area $(C_{a,0})$ satisfies

$$(4)\quad P_{a,0}C_{a,0} = \theta W_{a,0}L_{a,0}^h + (1-\theta)\rho\left[\left(W_{a,0}\bar{L} + \frac{1}{R_0^f}\frac{\overline{WL}}{\rho}\right) + \left(\frac{1+x_{a,0}}{1-\theta}\right)Q_0\right].$$

Here, the two terms capture spending by hand-to-mouth households and stockholders, respectively. The term in brackets illustrates the consumption wealth effect. With log utility, stockholders' consumption expenditure is a fraction of lifetime wealth, which consists of their human capital wealth (in parentheses) and their stock wealth. Their marginal propensity to consume (MPC) is given by ρ. In particular, a change in the price of capital Q_0 affects local consumption through the stockholders. We next solve for the equilibrium further, first in a benchmark case in which areas have common wealth and then by linearizing the equilibrium equations around that benchmark.

C. *Common Wealth Benchmark*

First suppose all areas have the same stock wealth, $x_{a,0} = 0$ for each a. In this case, the equilibrium allocations and prices are the same across areas, so we drop the subscript a. With symmetry and active monetary policy, hand-to-mouth labor supply is at its frictionless level everywhere. We choose parameters such that this level equals stockholders' exogenous labor, $L_0^h = \bar{L}$ [cf. equation (B.30) in the online Appendix]. Thus, the aggregate wages and labor satisfy

$$W_0 = \bar{W}, \qquad L_0 = L_0^h = \bar{L}.$$

Online Appendix B.3 characterizes the rest of the equilibrium and establishes

$$(5)\quad L_0^N/\bar{L} = \frac{1-\alpha^N}{1-\bar{\alpha}}\eta \quad \text{and} \quad L_0^T/\bar{L} = \frac{1-\alpha^T}{1-\bar{\alpha}}(1-\eta),$$

$$Q_0/\bar{W} = \frac{\bar{\alpha}}{1-\bar{\alpha}}\bar{L} + \frac{1}{R_0^f}\frac{D}{\rho},$$

$$R_0^f = \frac{1}{1-\rho}\frac{1-\bar{\alpha}}{1-(1-\bar{\alpha})\theta}\frac{(1-\theta)\bar{L}+D}{\bar{L}},$$

where

$$(6)\quad \bar{\alpha} = \eta\alpha^N + (1-\eta)\alpha^T.$$

Here, $\bar{\alpha}$ denotes the weighted average capital share across sectors. The first line shows that the share of labor employed in each sector is determined by the sectoral shares in household spending, adjusted by the differences in labor shares across sectors. The remaining lines characterize the equilibrium price of capital and the interest rate ("rstar").

We focus on the fluctuations in the price of capital Q_0 that result from changes in the *future* productivity of capital, D. Equation (5) illustrates that an increase in D increases Q_0 (despite the endogenous response of R_0^f) while leaving the *aggregate* labor market outcomes unchanged. We next investigate how this change affects *local* labor market outcomes.[29]

D. *Heterogeneous Wealth and Cross-Sectional Predictions*

Next consider the empirically relevant case of a heterogeneous distribution of stock wealth. To analyze this case, in online Appendix B.4 we log-linearize the equations that characterize the equilibrium around the common wealth benchmark for a given level of D. Specifically, we let $w_{a,0} = \log(W_{a,0}/\bar{W})$, $p_{a,0} = \log(P_{a,0}/P_0)$, and $l_{a,0} = \log(L_{a,0}/\bar{L})$ denote the log-deviations of nominal wages, nominal prices, and total labor for each area. We define $l_{a,0}^N$ and $l_{a,0}^T$ similarly for the nontradable and tradable sectors.

We first derive a reduced form labor supply relation. Log-linearizing hand-to-mouth agents' optimal labor supply, we obtain

$$w_{a,0} = \lambda\left(p_{a,0} + \varphi\, l_{a,0}\right) \qquad \text{where} \quad \varphi = \frac{\varphi^h}{\theta}. \tag{7}$$

Here, $\lambda \equiv \lambda_w/(1 + (1 - \lambda_w)\varphi^h \varepsilon_w) \in [0,1]$ is a meta-parameter that is an inverse measure of wage stickiness. When $\lambda = 0$, wages are fully sticky. When $\lambda = 1$, wages are fully flexible and the equation reduces to a neoclassical labor supply curve. The parameter, φ, is the effective inverse labor supply elasticity across all households. Since stockholders supply labor supply inelastically, the weighted-average labor supply elasticity is $1/\varphi = (1 - \theta) \times 0 + \theta \times 1/\varphi^h = \theta/\varphi^h$. We also have that local prices scale local wages,

$$p_{a,0} = \eta\left(1 - \alpha^N\right) w_{a,0}. \tag{8}$$

Combining equations (7) and (8), we obtain the reduced form relation

$$w_{a,0} = \kappa\, l_{a,0}, \qquad \text{where} \quad \kappa = \frac{\lambda\varphi}{1 - \lambda\eta\left(1 - \alpha^N\right)}. \tag{9}$$

[29] In online Appendix B.8, we generalize the model to incorporate uncertainty over D and show that our analysis is robust to other sources of fluctuations in Q_0, such as changes in the level of uncertainty or changes in risk aversion. Specifically, a reduction in households' perceived uncertainty about D increases Q_0 and R_0^f. With more general Epstein-Zin preferences, a decrease in households' relative risk aversion parameter increases Q_0 and R_0^f (see Proposition 4). Finally, conditional on generating the same increase in Q_0, the decline in risk or risk aversion has the same *quantitative* effects on local labor market outcomes as in our baseline model.

Here, κ is a composite wage adjustment parameter that combines the effect of inverse wage stickiness, λ, and the (effective) inverse labor supply elasticity, φ.

Our key predictions correspond to the comparative statics as the future productivity of capital changes from D^{old} to some D^{new}, giving rise to a change in the stock price of ΔQ_0:

$$\Delta\left(w_{a,0} + l_{a,0}\right) = \frac{1+\kappa}{1+\kappa\zeta}\mathcal{M}\left(1-\alpha^N\right)\eta\rho\frac{x_{a,0}\Delta Q_0}{\overline{WL}}, \tag{10}$$

$$\Delta l_{a,0} = \frac{1}{1+\kappa}\Delta\left(w_{a,0} + l_{a,0}\right), \tag{11}$$

$$\Delta\left(w_{a,0} + l_{a,0}^N\right) = \mathcal{M}(1-\bar{\alpha})\rho\frac{x_{a,0}\Delta Q_0}{\overline{WL}} + (\mathcal{M}-1)\frac{1-\alpha^T}{1-\alpha^N}\frac{1-\eta}{\eta}\Delta\left(w_{a,0} + l_{a,0}^T\right), \tag{12}$$

$$\Delta\left(w_{a,0} + l_{a,0}^T\right) = -(\varepsilon - 1)\left(1-\alpha^T\right)\Delta w_{a,0}, \tag{13}$$

where

$$\mathcal{M} = \frac{1}{1-\left(1-\alpha^N\right)\eta\left\{\frac{\theta\kappa+1}{\kappa+1} + \rho\frac{\kappa(1-\theta)}{\kappa+1}\right\}},$$

and

$$\zeta = 1 + (\varepsilon-1)\frac{\left(1-\alpha^T\right)^2}{1-\bar{\alpha}}(1-\eta)\mathcal{M}.$$

Here, $\Delta y \equiv y^{new} - y^{old}$ denotes the change in equilibrium variable y. In particular, $\Delta Q_0 = Q_0^{new} - Q_0^{old}$ denotes the dollar change in the aggregate stock wealth. Thus, $x_{a,0}\Delta Q_0$ denotes the change in stock wealth in area a relative to other areas. The equations describe how the (relative) stock wealth change normalized by the labor bill, $x_{a,0}\Delta Q_0/\overline{WL}$, affects the (relative) local labor market outcomes in the area.

These equations are intuitive. Equation (10) shows that an increase in stock wealth in an area increases the total labor bill. To understand the coefficient, note that one more dollar of stock wealth in an area leads to ρ dollars of additional total spending (cf. equation (4)), of which $\eta\rho$ is spent on nontradable goods produced locally. The increase in spending, in turn, increases the local labor bill by $(1-\alpha^N)\eta\rho$ dollars. This direct effect gets amplified by the local Keynesian income multiplier, denoted by $\mathcal{M}$.[30] The remaining term, $(1+\kappa)/(1+\kappa\zeta)$, reflects potential adjustments to the labor bill due to changes in exports to other areas. Specifically, an

[30] In the expression for the multiplier, the term in set brackets is a weighted-average of the MPC out of labor income of hand-to-mouth households (MPC of 1) and of stockholders (MPC of ρ). The weights $(\theta\kappa+1)/(\kappa+1)$ and $\kappa(1-\theta)/(\kappa+1)$ capture the extent to which additional labor income falls on hand-to-mouth households and stockholders. This depends not only on the population share θ but also on the wage adjustment parameter κ, because agents have different labor supply elasticities.

increase in local wages makes the areas's goods more expensive, which reduces (resp. increases) the tradable labor bill (and thus the total labor bill) when tradable inputs are gross substitutes, $\varepsilon > 1$ (resp. gross complements, $\varepsilon < 1$).

Equation (11) is a rearrangement of the reduced-form labor supply relation in (9). In particular, how much employment responds relative to the total labor bill (given a change in stock wealth) will discipline the wage adjustment parameter κ in our calibration exercise.

Equations (12) and (13) characterize the effects on the labor bill separately for the nontradable and tradable sectors. These equations are particularly simple when tradable inputs have unit elasticity, $\varepsilon = 1$. In this case, the effect on the tradable labor bill is zero, $\Delta(w_{a,0} + l_{a,0}^T) = 0$. We can then decompose the coefficient multiplying the wealth change for the nontradable labor bill into three terms: the direct household-level MPC out of stock market wealth ρ, the weighted average labor share of income $1 - \bar{\alpha}$, and the local multiplier $\mathcal{M}$. In Section V we use this decomposition to recover the household-level MPC given externally calibrated $1 - \bar{\alpha}$ and $\mathcal{M}$. Notably, the expression does not require information on the share of nontradables in spending η or the share of labor in the nontradable sector $1 - \alpha^N$ (see Section V for intuition).

When $\varepsilon \neq 1$, the decomposition for the nontradable sector does not hold exactly. In this case, as illustrated by equation (13), the stock wealth shock can affect the tradable labor bill if it has an effect on wages. As illustrated by equation (12), this affects local households' income and, therefore, creates knock-on effects in the nontradable sector. These knock-on effects depend on $\mathcal{M} - 1$. Intuitively, the direct impact of spending on tradables is absorbed by the tradable labor bill, but the multiplier effects are local and absorbed by the nontradable labor bill. However, if wages do not adjust much, then the tradable adjustment has a small impact on the analysis even when ε is somewhat different from 1.

E. *Summary and Mapping into the Empirical Analysis*

According to equations (10) to (13), an increase in *national* stock prices driven by, e.g., changes in expected *future* productivity of capital or in risk aversion, increases the *current* total labor bill and nontradable labor bill by more in areas with greater stock market wealth. The effect on the tradable labor bill is ambiguous and depends on whether tradable inputs are gross substitutes or complements. In online Appendices B.4 and B.5, we derive the additional predictions that nontradable labor, total labor, and wages weakly increase, and tradable labor weakly falls. All of these predictions accord with our empirical results.

The model also explains the functional form of our empirical regressions. In particular, define $S_{a,0} \equiv x_{a,0} Q_0 / \overline{WL}$ as area a's (relative) stock wealth divided by its labor bill and $R_0 \equiv \Delta Q_0 / Q_0$ as the stock return. Then, we have

$$S_{a,0} R_0 = \frac{x_{a,0} \Delta Q_0}{\overline{WL}}. \tag{14}$$

This variable corresponds to our main regressor, the change in the stock wealth of the area normalized by the local labor bill. Equations (10) to (13) illustrate that the empirical coefficients using this regressor have a tight mapping into the key parameters of the model.[31] We next exploit this mapping and provide a structural interpretation of our empirical findings.[32]

V. Calibration and Structural Interpretation

In this section, we use our empirical results from Section III to calibrate two key parameters of the model: the strength of the direct stock wealth effect, ρ, and the degree of wage adjustment, κ. We only need two model equations to recover these parameters. Therefore, our calibration also applies in richer models as long as these equations hold. Throughout, we choose the coefficients reported in Table 1 as our calibration targets. As shown in Figure 2, the first few quarters of the impulse response feature sluggish adjustment for reasons outside the model, due, e.g., to adjustment costs, consumer habit, or delayed recognition of the stock wealth changes, as found in Brunnermeier and Nagel (2008) and Alvarez, Guiso, and Lippi (2012). By quarter 7 adjustment is complete and the effect is relatively stable thereafter.

A. *Direct Stock Wealth Effect*

To determine the stock wealth effect parameter, we consider the nontradable labor bill in the special case with $\varepsilon = 1$ (cf. equations (12) and (14)),

$$\Delta\left(w_{a,0} + l_{a,0}^{N}\right) = \mathcal{M}(1 - \bar{\alpha})\rho \times S_{a,0}R_0, \tag{15}$$

where

$$S_{a,0} = \frac{x_{a,0}Q_0}{\overline{WL}}, \qquad R_0 = \frac{\Delta Q_0}{Q_0}.$$

Here, we interpret the denominator of $S_{a,0}$, $\overline{WL}$, as the labor bill *per year* as in the empirical implementation. Therefore, for calibration purposes we interpret the length of period 0 as one year and the parameter, ρ, as the MPC out of stock market wealth *per year*.[33]

In particular, the empirical coefficient can be decomposed into the product of three terms: the household-level MPC out of stock market wealth ρ, the weighted-average labor share of income $1 - \bar{\alpha}$, and the local Keynesian multiplier $\mathcal{M}$—equivalent to the multiplier on local government spending. We set the

[31] In the model, there is only one type of capital so all areas are associated with the same stock return, $R_{a,0} = R_0$ for each a. In the empirical exercise, we allow areas to have heterogenous risky portfolios and thus heterogeneous stock returns, $R_{a,0}$. Equations (10) to (13) would naturally generalize to a richer setting that features multiple risky assets and heterogeneous portfolios.

[32] As emphasized by Dynan and Maki (2001), such "dollar-dollar" specifications arise naturally in consumption-wealth models. An alternative approach would be to estimate an elasticity and to convert back into a dollar-dollar coefficient using the sample average ratio of stock market wealth to labor income (or consumption). This alternative has the drawback that the actual ratio varies substantially over time as the stock market booms and busts, a problem noted in the very different context of fiscal multipliers by Ramey and Zubairy (2018).

[33] We could estimate the MPC out of stock wealth over different horizons (by adjusting our regressor), as long as the horizon is sufficiently short that the supply side adjustment to a local demand shock is incomplete. Thus, we think of the length of period 0 as the time in which labor remains largely specific to the area and wages partially rigid following a demand shock.

weighted-average labor share to a value standard in the literature, $1 - \bar{\alpha} = 2/3$, and choose the nontradable share η and the hand-to-mouth share θ to achieve a multiplier $\mathcal{M} = 1.5$, in line with empirical estimates (Nakamura and Steinsson 2014, Chodorow-Reich 2019). We then calculate ρ by combining equation (15) with the empirical coefficient for the nontradable labor bill.

Specifically, using the coefficient from Table 1, we obtain

$$\mathcal{M}(1 - \bar{\alpha})\rho = \frac{\Delta\left(w_{a,0} + l_{a,0}^{N}\right)}{S_{a,0}R_0} = 3.23\%. \tag{16}$$

Substituting $1 - \bar{\alpha} = 2/3$ and $\mathcal{M} = 1.5$, yields

$$\rho = 3.23\%.$$

Hence, our estimates suggest that a one dollar increase in stock wealth increases household spending by about 3.23 cents per year (at a horizon of two years). The implied magnitude is in line with the yearly discount rates typically assumed in the literature. It is also close to the estimates of the stock wealth effect on consumption for wealthy households in Sweden estimated in Di Maggio, Kermani, and Majlesi (2020).

We make five remarks on this approach. First, it does not depend on the labor supply block of the model. Second, we do not have to parameterize the spending share of nontradables, η, or the labor share in the nontradable sector, $1 - \alpha^N$. To understand why, rewrite equation (15) as

$$\frac{\Delta\left(W_{a,0}L_{a,0}^{N}\right)}{\bar{W}L_0^N}\,\bar{W}L_0^N = \mathcal{M}\rho\left(1 - \alpha^N\right)\eta\left(x_{a,0}\Delta Q_0\right), \tag{17}$$

where

$$\frac{\bar{W}L_0^N}{\overline{WL}} = \eta\,\frac{1 - \alpha^N}{1 - \bar{\alpha}}.$$

This expression illustrates that the effect of stock market wealth on the nontradable labor bill *in dollars*, $\Delta(W_{a,0}L_{a,0}^{N})$, does depend on both η and $1 - \alpha^N$. However, with homothetic preferences and production across sectors, we have $\bar{W}L_0^N/\overline{WL} = \eta((1 - \alpha^N)/(1 - \bar{\alpha}))$: that is, the nontradable labor bill as a fraction of the total labor bill reflects the nontradable spending share as well as the sectoral differences in labor share. Therefore, since equation (15) normalizes the stock wealth change with the total labor bill, η and $1 - \alpha^N$ drop out of the equation. Intuitively, with homothetic preferences a sector's *average* share of the labor bill equals its *marginal* share of changes in the labor bill. As a consequence, the decomposition in (15) is robust to the nontradable spending share as well as to the sectoral differences in the labor share.[34] Moreover, since the decomposition does not depend on η, it applies as long as we observe the response in a subset of nontradable sectors.

[34] Equation (17) suggests the decomposition is also robust to (certain types of) cross-county heterogeneity in labor shares. For instance, suppose that areas with high stock wealth ($x_{a,0} > 0$) feature greater labor share in nontradables ($1 - \alpha_a^N > 1 - \alpha^N$)—perhaps because they spend more on high-quality goods that are more labor intensive as recently shown by Jaimovich, Rebelo, and Wong (2019). Then, the average labor bill of nontradables

Third, when $\varepsilon \neq 1$, equation (15) applies up to an adjustment [see equation (12)]. The adjustment reflects the possibility that the change in the tradable labor bill—due to the change in local wages—affects local households' income and creates knock-on effects on the nontradable labor bill. If wages are sufficiently rigid, then the tradable adjustment does not change the analysis by much even if ε is somewhat different from 1. In practice, the value we obtain for κ (described next) implies little loss of generality in ignoring this adjustment for empirically reasonable levels of ε, consistent with the small and statistically insignificant response of tradable payroll we estimate in the data. Therefore, we adopt $\varepsilon = 1$ as our baseline calibration in the main text and relegate the more general case to the online Appendix.[35]

Fourth, the simplicity of equation (16) makes it transparent to assess sensitivity to alternative targets for the labor share or local multiplier. For example, using a labor share of 0.6 and a local multiplier of 1.33 instead yields $\rho = 3.23/(0.6 \times 1.33) = 4.04$.

Fifth, we can compare our preferred ρ of 3.23 obtained from equation (16) to the ρ implied by the estimation using state-level consumption data. Following similar steps as in the derivation of equation (16) (see equation (B.87) in the online Appendix), we obtain

$$\Delta\left(p_{a,0} + c_{a,0}\right) = \mathcal{M}\rho \times S^{C}_{a,0} R_0. \tag{18}$$

Here, $p_{a,0} + c_{a,0}$ denotes log nominal consumption expenditure and $S^{C}_{a,0} = x_{a,0}\Delta Q_0/(P_0 C_0)$ denotes the ratio of area a's (relative) stock wealth change to its consumption expenditure. Notably, the labor share does not enter into equation (18). Using $\mathcal{M} = 1.5$ and the coefficient from Table 5, we obtain a nearly identical ρ of $4.82/1.5 = 3.21$.

B. *Wage Adjustment*

We use equation (11) to determine the wage adjustment parameter κ,

$$\Delta l_{a,0} = \frac{1}{1+\kappa}\Delta\left(w_{a,0} + l_{a,0}\right). \tag{19}$$

Recall that κ is a composite parameter that combines inverse wage stickiness and inverse labor supply elasticity [cf. equation (9)]. Therefore, it captures wage adjustment over the estimation horizon. One caveat is that, while the model makes predictions for total labor supply including changes in hours per worker, in the data we only observe employment. A long literature dating to Okun (1962) finds

in these areas is also greater than average ($\bar{W}L^{N}_{a,0} > \bar{W}L^{N}_{0}$). As long as the average labor bill is proportional to the labor share, $\bar{W}L^{N}_{a,0}/\bar{W}L^{N}_{0} = \eta((1-\alpha^{N}_{a})/(1-\alpha^{N}))$, equation (17) would still give the decomposition in (15).

[35] Specifically, in online Appendix B.6.2 we consider alternative calibrations with $\varepsilon = 0.5$ and $\varepsilon = 1.5$. In these cases, since trade adjustment affects the analysis, the implied ρ also depends on the share of tradables, η. We allow this parameter to vary over a relatively large range, $\eta \in [0.5, 0.8]$, and show that the implied ρ remains within 5 percent of its baseline level. As expected, the greatest deviations from the baseline occur when η is low (that is, when the area is more open).

an elasticity of total hours to employment of 1.5. Applying this adjustment and using the coefficients for total employment and the total labor bill from Table 1 yields

$$\frac{\Delta\, l_{a,0}}{S_{a,0} R_0} \;=\; 1.5 \,\times\, 0.77\%,$$

$$\frac{\Delta\left(w_{a,0} \,+\, l_{a,0}\right)}{S_{a,0} R_0} \;=\; 2.18\%.$$

Combining these with equation (19), we obtain

$$\kappa \;=\; 0.9. \tag{20}$$

Thus, a 1 percent change in labor is associated with a 0.9 percent change in wages at a horizon of two years.[36]

VI. Aggregation When Monetary Policy Is Passive

We next describe the effect of stock market changes on *aggregate* outcomes. In our model so far, these effects appear only in the interest rate ("rstar") because monetary policy adjusts to ensure aggregate labor supply remains at the frictionless level. We now consider an alternative scenario in which monetary policy is passive and leaves the interest rate unchanged in response to changes in stock prices. In this case, stock wealth changes affect aggregate labor market outcomes. These aggregate responses are of direct interest to monetary policymakers considering whether or not to accommodate a change in the stock market.

Our aggregation result for the labor bill is straightforward and relies on two observations. First, given homothetic preferences and production across sectors, a one dollar increase in stock market wealth has the same *proportional* effect on the *aggregate total* labor bill and the *local nontradable* labor bill, up to an adjustment for the difference in the aggregate and local spending multipliers. Second, for a wide range of parameters the aggregate spending multiplier in our calibration is greater than the local multiplier (this inequality also holds in many related models). Therefore, our empirical estimate of the effect on the local nontradable labor bill is a lower bound for the effect on the aggregate total labor bill. Notably, this aggregation result does not depend on any particular calibration of the local spending multiplier.

Our aggregation result for labor combines this finding with a third observation: since labor markets are local, the structural labor supply equation (7) remains unchanged as we switch from local to aggregate analysis (as emphasized by Beraja, Hurst, and Ospina 2016). The reduced form labor supply equation in (9) changes slightly because shocks impact aggregate inflation and local inflation differently.

[36] We can also estimate κ from the response of tradable employment [cf. equation (B.86) in the online Appendix]. Intuitively, tradable employment declines only insofar as local wages and prices rise, so the response of l^T provides information about κ. Auclert, Dobbie, and Goldsmith-Pinkham (2019) implement this approach in a different empirical setting. We prefer not to rely on this relationship because in practice (unlike in our model) even tradable goods may be influenced by local demand due to home bias, non-zero transportation costs, and supply chains. Nonetheless, the flat response of employment in the industries we classify as tradable in the data accords with a low value of κ.

Formally, let $\bar{R}_0^f$ denote the equilibrium interest rate in our earlier analysis corresponding to a particular level of productivity $\bar{D}$ [cf. (5)]. Suppose D changes but monetary policy keeps the nominal interest rate in period 0 constant at $\bar{R}_0^f$. In periods $t \geq 1$, monetary policy follows the same rule as before. Online Appendix B.7 characterizes the aggregate equilibrium variables in period 0, (Q_0, L_0, W_0, P_0). Log-linearizing this equilibrium around the frictionless benchmark, $D = \bar{D}$, we obtain closed-form solutions for the labor bill and labor that describe the effect of a change in stock wealth on *aggregate* labor market outcomes:

$$\Delta(w_0 + l_0) = \mathcal{M}^A (1 - \bar{\alpha})\rho \frac{\Delta Q_0^A}{\overline{WL}}, \tag{21}$$

$$\Delta l_0 = \frac{1}{1 + \kappa^A} \Delta(w_0 + l_0), \tag{22}$$

where

$$\mathcal{M}^A \equiv \frac{1}{1 - (1 - \bar{\alpha})\left\{\frac{\theta \kappa^A + 1}{\kappa^A + 1} + \rho \frac{(1 - \theta)\kappa^A}{\kappa^A + 1}\right\} - \bar{\alpha}\rho}$$

and

$$\kappa^A \equiv \frac{\lambda(\varphi + \bar{\alpha})}{1 - \lambda}.$$

Here, $l_0 = \log(L_0/\bar{L})$ and $w_0 = \log(W_0/\bar{W})$ denote log deviations of aggregate labor and wages from the frictionless benchmark. As before, $\Delta y \equiv y^{new} - y^{old}$ denotes the change in equilibrium variable y when expected future productivity of capital changes. The variable Q_0^A is the log-linear approximation to the exogenous part of stock wealth, $(1/\bar{R}_0^f)(\bar{W}D/\rho)$.[37] The parameters $\mathcal{M}^A$ and κ^A denote the aggregate multiplier and wage adjustment, respectively.

Equation (21) shows that the effect on the aggregate labor bill closely parallels its local counterpart (equation (11)), with three differences. First, the direct spending effect is greater in the aggregate than at the local level, $(1 - \bar{\alpha})\rho > \eta(1 - \alpha^N)\rho$. Intuitively, some spending falls on goods that are tradable across local areas but nontradable in the aggregate. Second, the aggregate labor bill does not feature the export adjustment term $(1 + \kappa)/(1 + \kappa\zeta)$. Third, the aggregate multiplier is different and (with our calibration) greater than the local multiplier, $\mathcal{M}^A > \mathcal{M}$. This is because spending on tradables (as well as the mobile factor, capital) diminishes the local but not the aggregate multiplier.[38]

[37] In our model, the price of capital satisfies $Q_0 = R_0 + (1/R_0^f)(\bar{W}D/\rho)$, where R_0 is the rental rate of capital [cf. (5)]. In this setting, a one dollar increase in $(1/R_0^f)(\bar{W}D/\rho)$ increases the equilibrium stock price, Q_0, by more than one dollar. This is because the increase in aggregate demand and output in period 0 also increases R_0. We focus on the comparative statics for a one dollar change in the exogenous component of stock wealth (as opposed to actual stock wealth) as the appropriate counterfactual scenario for what would happen if monetary policy did not react to an observed stock price shock in an environment where it usually stabilizes the demand effects of these shocks.

[38] In our model, there is a counteracting force when aggregate and local wage adjustment differ, $\kappa^A \neq \kappa$. Because of the simplifying assumption that stockholders supply labor less elastically than hand-to-mouth households, a smaller local wage adjustment ($\kappa < \kappa^A$) implies a lower share of additional labor income going to stockholders, who have a lower MPC, than in the aggregate. These distributional differences do not overturn the multiplier inequality in our model for a wide range of parameters (see online Appendix B.7 for details). The inequality $\mathcal{M}^A/\mathcal{M} \geq 1$ is a robust feature of settings with constrained monetary policy (Chodorow-Reich 2019).

Likewise, equation (22) shows that the reduced-form labor supply equation closely parallels its local counterpart (cf. equations (11) and (9)). In fact, since labor markets are local, the structural labor supply equation (7) that features the nominal price in addition to the nominal wage does not change as we switch from local to aggregate analysis. The difference stems from the equation for the nominal price, which is different than its local counterpart and given by $p_0 = (1-\eta)p_0^T + \eta p_0^N = \bar{\alpha}l_0 + w_0$. The aggregate price increases more than the wage, due to a fixed supply of capital in the aggregate. In contrast, the local price increases less than the wage, $p_{a,0} = \eta p_{a,0}^N = \eta(1-\alpha^N)w_{a,0}$ [cf. (8)], because only changes in the price of nontradables affect the local price level and because the local area faces a perfectly elastic supply of capital. Therefore, the real wage $w_0 - p_0$ decreases in the aggregate but increases locally, which creates a negative neoclassical labor supply response at the aggregate level and a positive one at the local level.

To quantify this difference, we rewrite the expressions for κ and κ^A to eliminate the wage stickiness parameter, λ, to obtain

$$\frac{1}{\kappa^A} = \frac{1}{1+\bar{\alpha}/\varphi}\left\{\frac{1}{\kappa} - \frac{1}{\varphi}\left(1-\eta\left(1-\alpha^N\right)\right)\right\}.$$

The extent to which the aggregate labor response is smaller than the local response depends on the Frisch elasticity $1/\varphi$ as well as the parameters $\bar{\alpha}, \eta, 1-\alpha^N$ (that determine the differences in price adjustment). Setting the Frisch elasticity $\varphi^{-1} = 0.5$ (Chetty et al. 2013), labor shares $1-\bar{\alpha} = 1-\alpha^N = 2/3$, and the nontradable share $\eta = 0.5$ (a conservative value), and substituting $\kappa = 0.9$ from (20), we obtain[39]

$$\kappa^A = 1.5. \tag{23}$$

Hence, our estimation and calibration imply that the aggregate labor response to a change in the aggregate labor bill is not too different than the corresponding local response despite the counteracting neoclassical effect.

We now use our estimates further to quantify the effect on the aggregate labor bill (which we then combine with (23) to describe the effect on aggregate labor). To relate equation (21) to our empirical estimates, we rewrite it as follows:

$$\Delta\left(w_0 + l_0\right) = \mathcal{M}^A\left(1-\bar{\alpha}\right)\rho \times S_0^A R_0^A, \tag{24}$$

where

$$S_0^A = \frac{Q_0^A}{WL_0} \quad \text{and} \quad R_0^A = \frac{\Delta Q_0^A}{Q_0^A}.$$

[39] As we have emphasized, the nontradable share of consumption expenditure η is a difficult parameter to calibrate given available regional data. Dupor et al. (2019) use the Commodity Flow Survey to estimate that two-thirds of shipments remain within a metropolitan area and 61 percent remain within a county. This estimate excludes the services component of consumption, which likely has a higher nontradable share. On the other hand, it may include some shipments within a local supply chain that eventually produces a tradable good. Our baseline calibration, $\eta = 0.5$, is conservative in the sense that a greater η would result in a smaller κ^A and a larger aggregate employment response. In online Appendix B.7, we consider a wider range, $\eta \in [0.5, 0.8]$, and show that the implied κ^A remains within 10 percent of our baseline calibration.

Here, S_0^A is the ratio of aggregate stock wealth to the aggregate labor bill and $R_0^A$is the shock to stock valuations. Hence, $S_0^A R_0^A$ is the aggregate analog of $S_{a,0} R_0$.

The coefficient in equation (24) is the same as its local counterpart in equation (15) for the *local nontradable* labor bill, up to an adjustment for the differences in the local and aggregate spending multipliers. Hence, we can combine our estimate for the local nontradable labor bill (for quarter 7) with the inequality $\mathcal{M}^A/\mathcal{M} \geq 1$ to bound the coefficient from below:

$$\mathcal{M}^A(1-\bar{\alpha})\rho = 3.23\%\left(\mathcal{M}^A/\mathcal{M}\right) \geq 3.23\%.$$

Therefore, if not countered by monetary policy, a one dollar increase in stock valuations increases the aggregate labor bill per year by at least 3.23 cents. Why does the effect on the *local nontradable* labor bill provide information about the implied effect on the *aggregate total* labor bill? With homothetic preferences and production technologies (and ignoring trade effects, $\varepsilon = 1$), a given amount of spending generates the same proportional change in the labor bill in *both* sectors. In particular, the proportional change in the labor bill in the nontradable sector—which we estimate with our local labor market approach—is the same as the proportional change in the labor bill in the tradable sector, which we cannot estimate directly due to demand slippage to other regions. Importantly, while clearly convenient for aggregation, the assumption of homotheticity across these broad sectors also has empirical grounding, as we demonstrated in Section IIIE.

We now describe the effect on aggregate labor. Equations (22) and (24) imply

$$\Delta l_0 = \frac{1}{1+\kappa^A}\Delta(w_0+l_0) = \frac{1}{1+\kappa^A}\mathcal{M}^A(1-\bar{\alpha})\rho \times S_0^A R_0^A \tag{25}$$

$$= \frac{3.23\%}{2.5}\left(\mathcal{M}^A/\mathcal{M}\right) \times S_0^A R_0^A.$$

Here, the second line substitutes $\kappa^A = 1.5$ [cf. equation (23)] and the response of the labor bill. Therefore, a one dollar increase in stock valuations increases aggregate labor (total hours worked) by the equivalent of at least 1.3 cents (i.e., the labor bill for the additional hours worked is at least 1.3 cents) if monetary policy does not respond.

We can combine these estimates with the ratio of aggregate stock wealth to the aggregate yearly labor bill, S_0^A, to obtain the responses to a stock return, R_0^A. Using data from 2015 (weighting counties by their income), we obtain $S_0^A = 2.67$.[40] Substituting this value into equations (24) and (25), we obtain

$$\Delta(w_0+l_0) = 3.23\%\left(\mathcal{M}^A/\mathcal{M}\right) \times 2.67 \times R_0^A \geq 8.6\% \times R_0^A,$$

$$\Delta l_0 = \frac{3.23\%}{2.5}\left(\mathcal{M}^A/\mathcal{M}\right) \times 2.67 \times R_0^A \geq 3.45\% \times R_0^A.$$

[40]This value coincides almost exactly with the corresponding ratio of 2.63 obtained using C-corporation equity wealth in the FAUS and total wages and salaries in NIPA.

Therefore, if not countered by monetary policy, a 20 percent stock return (approximately the yearly standard deviation of the return on the market portfolio) would increase the aggregate labor bill by at least 1.7 percent, and aggregate hours by at least 0.7 percent, at a horizon of two years.[41]

VII. Conclusion

We estimate the effect of stock market wealth on labor market outcomes by exploiting regional heterogeneity in stock wealth across US counties. An increase in stock wealth in a county increases local employment and the labor bill, especially in nontradable industries but also in total, but does not increase employment in tradable industries. The analysis is robust to MPC heterogeneity across stockholders because in the data stock wealth heterogeneity is substantially greater within than across counties. We develop a theoretical model to convert the estimated local general equilibrium effect into a household-level MPC out of stock market wealth of around 3.2 cents per year. We also calculate the aggregate general equilibrium effects of the stock wealth consumption channel on the labor market: a 20 percent change in stock valuations, unless countered by monetary policy, affects the aggregate labor bill by at least 1.7 percent and aggregate hours by at least 0.7 percent two years after the shock.

Our findings that stock price changes affect labor market outcomes support "the Fed put"—the tendency for central banks to cut interest rates after stock market declines unrelated to productivity (see, e.g., Rigobon and Sack 2003, Bjørnland and Leitemo 2009, Cieslak and Vissing-Jorgensen 2017). Specifically, our estimates and aggregation results can be used to calibrate the appropriate interest rate response. If the interest rate is constrained, e.g., due to the zero lower bound or fixed exchange rates, then our analysis implies that stock price declines would induce a sizable reduction in aggregate labor bill and employment (see Caballero and Simsek 2020 for a related dynamic setup that illustrates the downturn would be further amplified by feedbacks between output and asset prices).

An important question for policymakers concerns the speed at which stock wealth changes affect the economy. We find evidence of sluggish adjustment, with the effect on labor markets starting after 1 to 2 quarters and stabilizing between quarters 4 and 8. This pattern suggests that large stock price declines that quickly reverse course (such as the stock market crash of 1987 or the Flash crash of 2010) are unlikely to impact labor markets. In contrast, more persistent price changes (such as the NASDAQ boom in the late 1990s or the stock market boom during the recovery from the Great Recession) have more sizable effects.

On the other hand, our focus on the consumption channel and our empirical design omit factors that could further increase the effect of stock market wealth changes on aggregate labor markets. First, as discussed by Chodorow-Reich (2019), the

[41] The magnitude of this calculation changes slightly if we instead assume consumption only responds to changes in taxable stock wealth. In that case, we would recover a larger marginal effect on payroll (intuitively, a larger consumption response would be required to rationalize the same cross-county changes in labor income given smaller wealth), but we would multiply that response by a smaller change in wealth given a 20 percent change in the stock market. Combining these changes, we would find that a 20 percent stock return increases the aggregate labor bill by at least 1.3 percent.

Keynesian multiplier effects are likely greater at the aggregate level (when monetary policy is passive) than at the local level. Second, other channels, such as the response of investment, also create a positive relationship between stock prices and aggregate demand (see Caballero and Simsek 2020). Relatedly, while our industry-level analysis mostly focuses on sectors that produce nondurable goods and services, we also find that stock price changes have a large effect on the construction sector. The construction response provides further qualitative evidence that stock wealth affects the economy by changing local demand and inducing an accelerator-type effect on housing investment (see Rognlie, Shleifer, and Simsek 2018; Howard 2017). We leave a quantitative assessment of these additional factors for future work.

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