Corporate Payouts and Local Job Creation[*]

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Abstract

Corporate payouts have surged sharply in recent decades, fueling ongoing debates over their economic consequences. This paper examines the impact of corporate dividend payouts on local job creation. Using the IRS county-level dividend income data and a shift-share instrument, I find that household dividend income is positively associated with local job creation, particularly among small and young firms. I validate this finding by implementing a difference-in-differences design to exploit the large special dividends in 2010Q4 and 2012Q4 before the dividend tax rate was scheduled to rise. The effects operate through two channels: consuming or depositing dividends, which in turn fuels small business lending. These findings suggest that capital flowing from mature firms to small businesses can stimulate economic growth, challenging recent calls to restrict corporate payouts.

Keywords: Corporate Payouts, Dividends, Job Creation, Special Dividends, Consumption, Bank Deposits

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1 Introduction

U.S. public corporations have substantially increased payouts over the past several decades, particularly since the 2000s, as shown in Figure 1.[1] This sharp rise in payouts has sparked ongoing debate about their broader economic consequences. Critics argue that rising payouts contribute to wealth inequality and stagnant wage growth (e.g., Palladino, 2018a,b), as they disproportionately benefit wealthy households, who are more likely to reinvest the proceeds in financial markets rather than spend them in the real economy. However, recent studies (e.g., Fried and Wang, 2018; Guest, Kothari, and Venkat, 2023; Ikenberry, Vermaelen, and Zhou, 2024) challenge this view, suggesting that the negative impact of corporate payouts may be overstated. Rather than simply enriching wealthy shareholders, corporate payouts can facilitate capital reallocation from mature firms to younger and smaller businesses, thereby fostering economic dynamism.[2] Motivated by this debate, this study investigates how corporate payouts affect local labor job creation and entrepreneurial activity.

Theoretically, the effects of corporate payouts on employment and jobs are *ex-ante* ambiguous. On the one hand, households have long been documented to exhibit a strong tendency to consume dividend income and low propensity to reinvest it (Baker, Nagel, and Wurgler, 2007; Hartzmark and Solomon, 2019; Di Maggio, Kermani, and Majlesi, 2020; Bräuer, Hackethal, and Hanspal, 2022). Consumption, as a primary driver of economic activity, is widely documented to support job creation (Fatás and Mihov, 2001). Additionally, a substantial share of corporate payouts is deposited into banks (Lin, 2021), which can, in turn, expand local credit supply to firms (Gilje, 2019). Since small businesses heavily rely on bank financing (Petersen and Rajan, 1994; Chodorow-Reich, 2014), the greater credit supply due to increased deposits can stimulate job creation.[3]

[1] Two widely documented explanations are increased firm profitability and payout rates (Kahle and Stulz, 2021; Michaely and Moin, 2022) and decreased corporate and investor tax rates (Brav, Graham, Harvey, and Michaely, 2005; Chetty and Saez, 2005; Albertus, Glover, and Levine, 2025).

[2] For example, Fried and Wang (2018) state that "*some of the capital flowing to S&P 500 shareholders is then reinvested in smaller public companies and private firms, fueling growth and employment outside the S&P 500.*" Similarly, Kevin Hassett, former chairman of the White House Council of Economic Advisers, warned that restricting buybacks could trap capital within older firms and stifle entrepreneurship. Source: `https://www.cnn.com/2019/03/01/investing/stock-buybacks-hassett-trump/index.html`.

[3] An illustrative case comes from Alaska, which began paying residents a $1,000 annual dividend in 1982,

On the other hand, unlike regular income, which is broadly distributed across the population, dividend income is concentrated among wealthy households who are less likely to adjust consumption in response to additional income (Auerbach and Hassett, 1989; Arrondel, Lamarche, and Savignac, 2015). This fact weakens the consumption channel as a mechanism linking corporate payouts to local employment. On the credit supply side, dividend income may enter the banking system as deposits. However, this channel operates only if local banks are deposit-constrained and unable to fund all positive NPV projects using external financing (Diamond and Rajan, 2001; Paravisini, 2008; Gilje, Loutskina, and Strahan, 2016). In areas dominated by large or nationally funded banks, local deposits are less likely to be binding constraints. Generally,wealthy households are more likely to reside in such regions, further weakening the deposit channel. Therefore, while both channels are theoretically valid, the magnitude of their effects on local employment is ambiguous and requires empirical investigation.

My analysis exploits county-level dividend income data from the IRS and employment data from the Census Bureau covering the period 1990–2020. The baseline regression examines the impact of dividend income on job creation, job destruction, and net job creation in the following year. After controlling for other sources of income, county characteristics, and including state×year and county fixed effects, I find that a \$1 million increase in total dividend income is associated with 2.62 additional jobs created and 1.28 fewer jobs destroyed, resulting in a net gain of 4.06 jobs. The employment effect is roughly ten times larger than that associated with a \$1 million increase in regular income. This finding is consistent with prior literature showing that the marginal propensity to consume and to deposit out of dividends is higher than out of regular income.

To mitigate confounding effects from unobserved county-specific factors, I construct a shift-share instrumental variable for dividend income by interacting each county's predetermined share of national dividends with aggregate dividends in each year. This instrument represents predicted dividend income under the assumption that a county's share of national dividends remains fixed over time and that all variation arises from aggregate shocks to corporate pay-

funded by oil revenues. Knapp, Goldsmith, Kruse, and Erickson (1984) report that recipients spent over half the dividend and saved \$200, adding \$360 million to consumer purchasing power and creating about five thousand jobs in 1983.

outs, such as tax policy changes or broad increases in payout activity. The IV estimation yields robust results, with coefficients larger than those in the baseline specification. Further analyses show that the main findings remain robust when accounting for alternative sources of confounding, including local economic level and growth, business vitality, local credit supply to small businesses, education level, house price growth, and the presence and growth of public firms.

Investors may exhibit dynamic changes in their tendency to consume, deposit, or reinvest dividend income. In addition, Müller-Dethard, Reinhardt, and Weber (2025) show that the evolution of brokerage settings—such as whether dividends are distributed to a bank checking account or retained in a brokerage cash account—can act as a nudge influencing investors' use of the proceeds. As a result, the employment effect of dividend income on job creation may vary over time. Consistent with increasing retention of dividends in brokerage cash accounts (Müller-Dethard et al., 2025), I find that the effect declined around 2000 but has remained persistent since. This pattern suggests that the market has reached a relative equilibrium in how dividends are allocated across consumption, deposits, and reinvestment, and that dividend income continues to play an important role in job creation today.

To strengthen causal identification, I implement a difference-in-differences analysis by exploiting a historically large surge in special dividend payments triggered by the scheduled expiration of the 2003 dividend tax cut and the anticipated increase in dividend tax rates at the end of 2010 and 2012. These special dividends were largely driven by intertemporal tax arbitrage rather than firm fundamentals or local economic conditions, providing a plausibly exogenous setting to address endogeneity concerns. Consistent with the local investment bias literature, I first document that counties with firms paying special dividends hardhearted in 2010Q4 and 2012Q4 experienced significantly larger increases in dividend income compared to counties with public firms that did not issue special dividends. I then show that these counties also experienced greater net job creation during 2010–2015, with no comparable effects in the years before or after this period. These results reinforce the main findings and lend further support to the causal interpretation of the estimated employment effects of dividend income.

The mechanism analyses support both the consumption and deposit channels. Using total sales in nontradable sectors (*i.e.*, retail and food services) as a proxy for local consumption, I find that dividend income is positively associated with consumption, but not with sales in other sectors. This finding is consistent with the fact that revenues in nontradable sectors are more directly tied to local consumer demand. If the consumption channel were the sole mechanism, the employment effects should be concentrated in nontradable sectors. However, I observe a positive relationship between dividend income and net job creation across nontradable, tradable, and other sectors, suggesting that consumption is not the primary channel through which dividend income affects local employment.

I next turn to examine the deposit channel analysis. I first document that dividend income is positively associated with county-level aggregate deposit growth. Building on this evidence, I further examine whether the increase in deposits translates into greater small business lending, which is crucial to local businesses. Bank theory holds that rising deposits stimulate lending if (1) firms depend on bank financing, and (2) banks rely on local deposits and cannot readily reallocate capital through internal bank markets (Gilje et al., 2016; Gilje, 2019). These conditions are likely met given two facts: (1) the majority of establishments are small, which are highly reliant on bank loans (Petersen and Rajan, 1994; Chodorow-Reich, 2014); and (2) most banks are regional and only operate in one county.

Consistent with these findings, I show that dividend income is positively associated with local small business lending. This effect is more pronounced for small firms than for large ones, and a larger proportion of the increase in loans is in small amounts (*i.e.*, under $100,000). I further find that the positive effect of dividend income on net job creation is concentrated among small (*i.e.*, fewer than 20 employees) and young (*i.e.*, five years old or younger) establishments. These results suggest that increased dividend income disproportionately benefits lending to establishments that rely more heavily on bank financing. A cross-sectional test across sectors with varying degrees of bank dependence supports this conclusion.

According to the Small Business & Entrepreneurship Council, small businesses have accounted for 62% of net new job creation since 1995.[4] However, the employment share of these firms has declined substantially in recent decades (Autor, Dorn, Katz, Patterson, and

[4]Source: https://sbecouncil.org/about-us/facts-and-data/.

Van Reenen, 2020). In this context, my findings are practically meaningful: they suggest that corporate payouts serve as a transmission channel through which capital from large public firms flows to small businesses, thereby promoting job creation among them.

My final analysis examines heterogeneity by local bank size and geographical reach. As discussed earlier, large or conglomerate banks can reallocate capital internally across regions, making them less dependent on local deposit inflows and thus less financially constrained in their lending decisions. In contrast, small and regional banks rely more heavily on local deposits and are therefore more exposed to local credit supply shocks (DeYoung, Gron, Torna, and Winton, 2015). Consistent with this view, I find that the main effect is significantly larger in counties with a greater presence of small and regional banks.

Overall, my mechanism analyses support the view that both consumption and deposit channels play a role in explaining the positive effect of dividend income on local job creation. The empirical evidence, however, leans more strongly toward the deposit channel as the dominant mechanism.

The paper contributes to the literature in the following four aspects. First, this paper relates to the strand of studies on investors' responses to dividend income. The classic "dividend irrelevant" theory (Miller and Modigliani, 1961) believes that corporate payouts do not affect the firm's value and investors' total wealth in a perfect market. Since the stock price drops the same as the amount dividends per share, investors should view dividends the same as retained earnings. However, in a frictional world, investors tend to use separate mental accounts to track stock price changes and dividends (Thaler, 1980; Hartzmark and Solomon, 2019). As a result, investors display a strong propensity to consume dividend income rather than reinvest it (Baker et al., 2007; Hartzmark and Solomon, 2019; Bräuer et al., 2022).[5] In addition to consuming or reinvesting dividends, a concurrent study by Lin (2021) finds that a large portion of corporate payouts flows into the banking sector as deposits.[6] Although there is extensive re-

[5] Table A.2 summarizes household consumption and reinvestment rates in prior papers. Most papers document a higher consumption rate than reinvestment rate. The exception is Müller-Dethard et al. (2025), whose data from a German brokerage where dividends are automatically deposited into brokerage cash accounts. The authors argue that this default effect outweighs the mental accounting effect.

[6] Using Swedish household data, Di Maggio et al. (2020) also find households deposit 4%-14% dividends into bank account.

search on household responses to dividend income, no study has examined its broader economic implications. This paper fills that gap by showing that dividend income positively affects local employment, particularly among small and young firms. The findings suggest that investors act as intermediaries, channeling capital from large, mature firms to local entrepreneurial activity.

Second, this study contributes to the literature on the spillover effects of public firms on economic growth. A growing body of research examines how initial public offerings (IPOs) affect the local economy. Butler, Fauver, and Spyridopoulos (2019) and Hartman-Glaser, Thibodeau, and Yoshida (2023) find that IPOs raise house prices and stimulate consumer spending, thereby generating employment. In contrast, Cornaggia, Gustafson, Kotter, and Pisciotta (2024) document a negative relation between IPOs and local employment growth. Other studies highlight that public firms' disclosures improve information quality and reduce investment uncertainty within their industries, thereby enhancing peer private firms' investment (Badertscher, Shroff, and White, 2013) and fostering new business formation (Barrios, Choi, Hochberg, Kim, and Liu, 2021).

Public firms' stock price performance also affects the economy. For example, Di Maggio, Kermani, Ramcharan, Yao, and Yu (2022) find that firms cut employees' wage in a period of high stock price uncertainty and employees reduce durable consumption as a response. A close paper, Lin (2020), shows that households withdraw deposits during stock market booms, leading to a decline in bank lending and thereby reducing employment in bank-dependent sectors. The contrasting findings in my paper are consistent with mental accounting theory that investors treat dividend income differently from capital gains. While stock price appreciation draws capital away from the local banking system, public firms can also generate positive spillover effects by distributing cash to shareholders, which ultimately flows into small businesses.

Third, my study adds to the literature on bank and real economy. Existing literature consistently finds that banks have a positive impact on the real economy (Berger, Molyneux, and Wilson, 2020). However, differences in bank specialization lead to heterogeneous effects across firm types. Specifically, small and regional banks play a more significant role in the local economy than large banks (Petersen and Rajan, 1994; Hakenes, Hasan, Molyneux, and Xie, 2015; Gilje, 2019), as they often specialize in relationship lending that depends on "soft" information, mostly with small and young firms. Focusing on local market enables small banks easily access to such information and helps sustain lending relations (Petersen and Rajan, 2002). My finding—the effect of dividend income on small business lending and job creation is stronger for small and young firms, and more pronounced in counties dominated by small banks—highlights the importance of small businesses and regional banks for local economic development (Hakenes et al., 2015). It has important implications at the current stage, marked by the rise of large firms (Autor et al., 2020) and the decline in the share of community banks.[7]

Lastly, the paper provides a novel perspective on the economic implication of rising high-income households. Recent studies (Auclert and Rognlie, 2017; Mian, Straub, and Sufi, 2020) document a rise in aggregate household savings, driven by the higher saving rates of high-income households. The increased savings by the top 1% households lower interest rates and help finance borrowing by lower-income households. However, Doerr, Drechsel, and Lee (2024) argue that high-income households primarily allocate their savings to stocks and bonds and hold a lower bank deposit rate than low-income householders. This saving pattern, coupled with rising top income shares, benefits firms with capital market access but reduces job creation among bank-dependent firms. Given that stock investors are generally rich, my finding that dividend income boosts bank deposits and supports employment offers a novel channel through which wealthy households contribute to the real economy.

2 Data and Summary Statistics

2.1 Data Source

Dividend income. I download county-level dividend data from the IRS Statistics of Income (SOI) program, which reports the aggregate income information reported on individual income tax returns filed with the IRS since 1989. The dividend income includes distributions from private and public C-corporations but excludes those from partnerships, S-corporations, and

[7] The share of community banks in total banking assets has declined to below 15% as of 2023, while the five largest commercial banks now hold nearly half of total banking assets. Source: `https://www.kansascityfed.org/banking/community-banking-bulletins/the-critical-role-of-community-banks/`.

trusts, which are instead taxed as ordinary income.

Jobs and establishment. Following Mian and Sufi (2014), I obtain the county-level aggregate employment and payroll data from the County Business Patterns (CBP) published by the U.S. Census Bureau.[8] I also complement the county-level business dynamic data from the Census Bureau's Business Dynamics Statistics (BDS) Program. The BDS tracks annual job creation, destruction, establishment entry, and exit for all private, non-agricultural establishments since 1978 (Decker, Haltiwanger, Jarmin, and Miranda, 2014). The detailed breakdown by sector, firm age, and firm size enables granular-level analyses on potential heterogeneous effects. Both datasets cover the period from the week of March 12 in the prior year to the week of March 11 in the current year. Due to reporting lags, I use a one-year forward measure for job creation and establishment entry variables. Specifically, these variables reflect changes occurring between March 12 of year t and March 11 of year $t+1$.

Other county-level variables. I obtain county-level additional demographic and economic variables from various sources. Income and population data are accessed from the Bureau of Economic Analysis's Regional GDP and Personal Income reports. The employment and unemployment labor force information used to calculate the unemployment rate is provided the Bureau of Labor Statistics' (BLS) Local Area Unemployment Statistics (LAUS) program. Table A.1, Panel A lists the county-level variable definitions and sources.

2.2 Empirical Design

2.2.1 OLS Estimation

To estimate the impact of corporate payouts on local job creation, I estimate the following OLS model:

$$\frac{Net\ Job\ Creation_{i,t+1}}{Emp_{i,t}} = \beta \frac{Dividends_{i,t}}{Emp_{i,t}} + \gamma' X_{i,t} + \eta_i + \mu_{s,t} + \epsilon_{i,t}. \tag{1}$$

[8]The CBP covers employment at establishments with an Employer Identification Number (EIN). It excludes self-employed individuals, employees of private households, railroad employees, agricultural production employees, and most government employees. Thus, it offers better coverage of businesses than BEA data, which measure all jobs in a county.

Following Engelberg, Guzman, Lu, and Mullins (2025) and Lindsey and Stein (2025), my primary outcome variable for county-level business dynamics is net job creation scaled by employment, *Net Job Creation/Emp*. Net job creation is defined as the difference between newly created jobs (*Job Creation*) and eliminated jobs (*Job Destruction*). This variable measures the change in net jobs compared with the existing jobs, which can also be called net job creation rate. The key explanatory variable is county-level dividend income scaled by employment (*Dividends/Emp*). The variable of interest β. Based on my hypotheses outlined earlier, I expect β to be positive. Since both job and dividend variables are scaled by the same denominator, β can be interpreted the number of change in net job creation associated with a \$100,000 increase in dividend income.[9]

I lag dividend income and other covariates by one year to account for the possibility that it takes time for dividends to translate into job creation. For instance, banks may take several months to review loan applications and allocate newly available deposits to firms.[10] As noted earlier, employment and establishment counts are measured in March of year t. Job creation and establishment entry are measured from March of year t to March of year t+1, capturing the number of new jobs and new establishments created during that interval.

As dividend income is typically highly correlated with regular income, controlling for it is crucial to isolate the effect of dividends. I measure regular income as the difference between total income and dividend income, scaled by employment (*Other Income/Emp*). Dividend income is also positively associated with capital gains. Chodorow-Reich, Nenov, and Simsek (2021) show that households' stock market wealth is positively associated with consumption, which can stimulate local employment and payroll. To isolate the effect of dividend payouts from unrealized capital gains, I follow Lin (2020, 2021) by including an interaction between the county-level dividend-to-income ratio (*Div Ratio*) and the CRSP annual stock market return excluding dividends (*Return*). The *Div Ratio* serves as a proxy for local stock market partici-

[9]Dividend income is measured in thousands of dollars, and job variables are expressed in percentage points.

[10]It is possible that the effects materialize within the same year as the dividend payment, as households often increase consumption shortly after receiving dividends (Bräuer et al., 2022). However, since businesses may wait to confirm whether the demand shock is persistent before making hiring decisions, using a one-year lag is a more conservative approach. It is worth noting that all results are robust to measuring jobs in the same year as the dividend income.

pation, and the interaction term, *Div Ratio* $\times$ *Return*, captures variation in unrealized capital gains.

I also control for a vector of demographic and economic variables to capture cross-county heterogeneity. Specifically, I include the log of population ($Ln(Population)$) and population growth rate ($Population\ Growth$). The county-level unemployment rate ($Unemployment\ Rate$) accounts for local labor market conditions. I also include the share of the population above age 65 (*Age Above 65*), as old people are more likely to hold dividend-paying stocks (Becker, Ivković, and Weisbenner, 2011) and are less likely to participate in the labor force. Some counties,such as those in the Bay Area, naturally exhibit stronger business environments and higher dividend income due to the presence of publicly listed firms headquartered there. I include county fixed effects (η_i) to account for such time-invariant local characteristics. Moreover, I include state$\times$year fixed effects ($\mu_{s,t}$) to absorb state-level time-varying factors, such as changes in tax policy or macroeconomic conditions. I cluster standard errors at the county level to control for within-county serial correlations.

2.2.2 IV Estimation

The baseline OLS regression may yield biased estimates due to unobserved local factors or reverse causality. For example, county-level wealth shocks, such as natural resource discoveries or natural disasters, may simultaneously affect both stock market participation (and thus dividend income) and job creation through wealth effects. To mitigate these endogeneity concerns, I adopt an instrumental variable (IV) strategy based on a shift-share design that isolates plausibly exogenous variation in county-level dividend income.

Following the shift-share design (e.g., Bartik, 1991; Borusyak, Hull, and Jaravel, 2025), I construct an instrument for dividend income by interacting each county's predetermined dividend share with national dividends in each year. This instrument is a predicted dividend income assuming each county's share of national dividends remains fixed and that variation arises solely from changes in aggregate corporate payouts. The key idea is that county-level dividend income is determined by both national shocks, such as dividend tax changes or aggregate payout trends, and contemporaneous local shocks. The latter affects the concurrent dividend share. For example, a dividend-paying firm reallocating to a county can bring abnormal dividend income than before, thus increasing the dividend share. By using a lagged dividend share, which is typically persistent and plausibly exogenous to future local shocks, the instrument removes the influence of contemporaneous county-specific shocks and isolates the exogenous component driven by national dividend fluctuations.

Specifically, the instrument for $Dividends_{i,t}$ is as follows:

$$Dividends_{i,t}^{Proj} = \frac{Dividends_{i,1989}}{\sum_{j \neq i} Dividends_{j,1989}} \times \sum_{j \neq i} Dividends_{j,t}, \tag{2}$$

where $\sum_{j \neq i} Dividends_{j,t}$ is the total dividends in all other counties in year t. $\frac{Dividends_{i,1989}}{\sum_{j \neq i} Dividends_{j,1989}}$ represents the county's initial dividend share in 1989 (the first year with IRS data, and one year before the sample begins), which captures a county's exposure to the national dividend trends. The dividend share is persistent over time, as displayed in Figure A1. For example, the 10-year autocorrelation is about 0.95, and even at a 30-year lag, it remains high at approximately 0.92. Thus, I use the predeterminated share following the common standard in the shift-share literature to reduce the potential bias raising from the contemporaneous factors can affect the share and other key variables.

The two-stage estimation equations are as follows:

$$\begin{aligned} \text{1st stage:} \quad & \frac{Dividends_{i,t}}{Emp_{i,t}} = \kappa \frac{Dividends_{i,t}^{Proj}}{Emp_{i,t}} + \gamma' X_{i,t} + \eta_i + \mu_s, t + \epsilon_{i,t}, \\ \text{2nd stage:} \quad & \frac{Net\ Job\ Creation_{i,t+1}}{Emp_{i,t}} = \beta \frac{\widehat{Dividends}_{i,t}}{Emp_{i,t}} + \gamma' X_{i,t} + \eta_i + \mu_s, t + \varepsilon_{i,t}. \end{aligned} \tag{3}$$

$\frac{\widehat{Dividends}_{i,t}}{Emp_{i,t}}$ is the predicted value in the first stage. As in Equation 1, I control for county and state-by-year fixed effects, along with a set of county-specific covariates.

A valid instrument must satisfy two assumptions: relevance and the exclusion restriction. For relevance, the instrument should be strongly correlated with realized county-level dividend income. It is likely to hold because dividend shares are highly persistent. In addition, most of the variation in county-level dividends over time is plausibly driven by national-level shocks, such as aggregate changes in corporate payouts, rather than by local shocks. To assess this, I calculate the residual component of dividend income, $Dividends_{i,t}^{Res}$, as the difference between realized dividends and their projected values from the shift-share instrument, $Dividends_{i,t}^{Proj}$.

Table A.3 reports correlations among these three dividend variables and three aggregate payout measures: total dividends, net repurchases (repurchases minus equity issuance), and total net payouts by all Compustat firms. The correlation between $Dividends$ and $Dividends^{Proj}$ is high (0.937), while the correlation between $Dividends$ and $Dividends^{Res}$ is much lower (0.366), suggesting that most of the time-series variation in county-level dividend income is captured by the national component. Consistent with this interpretation, $Dividends^{Proj}$ is significantly correlated with all three aggregate payout measures, while $Dividends^{Res}$ shows no significant correlation with any of them. These results suggest that my instrument sufficiently isolates variation driven by national shocks and excludes county-specific factors, satisfying the relevance condition of the IV strategy.

The exclusion restriction requires that the instrument affects local job creation only through its impact on dividend income. Although the dividend share is endogenous, its high persistence allows county fixed effects to absorb much of the time-invariant local variation. Furthermore, because the share is measured before the start of the sample period, it is unlikely to correlate with omitted determinants of job creation in later years, particularly given that the sample spans over 30 years and controls include county fixed effects and county-level fundamentals.[11]

For the exclusion restriction regarding the shift component, national dividend component in my paper, Borusyak et al. (2025) propose the conditional exogeneity assumption. In particular, the instrument is valid if the national dividend trend is uncorrelated with the county-specific shocks, conditional on controls and fixed effects. Formally, in my setting, the following condition must hold:

$$E\{(\sum\nolimits_{j\neq i} Dividends_{j,t}) \cdot \varepsilon_{i,t} | X_{i,t}, \eta_i, \mu_s, t\} = 0. \tag{4}$$

Several design features support this assumption. First, the national dividend component excludes county i's own dividend income, preventing mechanical correlation with unobserved local shocks. Second, while national dividend income may comove with macroeconomic trends such as GDP growth or interest rate, these aggregate factors are absorbed by year fixed effects.

[11] It is possible that unobserved trends influence both the 1989 dividend share and job creation in the early years of the sample. Notably, IV results remain robust when excluding the 1990–1995 subsample.

Third, fundamental county-level controls help account for time-varying local dynamics. For instance, unemployment rates capture local economic conditions and population growth reflects demographic trends that affect both the demand and supply of new jobs. Taken together, these controls and fixed effects help ensure that the residual variation in national dividend income is plausibly orthogonal to other determinants of local job creation.

2.3 Summary Statistics

The final county-level sample includes 3,083 counties from 1990 to 2020.[12] I winsorize all variables at the 1st and 99th percentiles to mitigate the influence of outliers. Dollar-denominated variables are adjusted for inflation and expressed in 2020 constant dollars. Table 1 reports summary statistics for the main variables.

From 1990 to 2020, the average U.S. county had approximately 82,763 residents and 31,511 private non-agricultural employees. On average, local establishments created jobs equal to 14% of current employment (4,438) and eliminated 13% (4,091), resulting in an annual net job creation rate of 0.96% (366). These figures reflect the high level of business dynamism and job reallocation observed in the U.S. economy (Davis and Haltiwanger, 1992). Average county-level dividend income was \$1.4 thousand, compared to other income per employee of \$163.7 thousand. These distributions are right-skewed, as medians are lower than the corresponding means.

Regarding other county characteristics, the average annual employment growth rate was 1.6%, dividend income accounted for 1.6% of adjusted gross income (*Div Ratio*), the average unemployment rate was 6.1%, and 16.1% of the population was aged 65 or older.

[12]Unemployment data begins in 1990. Job and employment data ends in 2022 March, but using a one-year lead limits the sample to 2020 for other variables

3 Baseline Results

3.1 The Effect of Dividends on Job Creation

Table 2 reports the OLS regression results for the baseline test specified in Equation 1. The dependent variables are *Job Creation/Emp* in Columns (1) and (2), *Job Destruction/Emp* in Columns (3) and (4), and *Net Job Creation/Emp* in Columns (5) and (6). Columns (1), (3), and (5) include dividend income, other income, and fixed effects only, while Columns (2), (4), and (6) additionally control for other county-level covariates. The coefficients of *Dividends/Emp* are positive when the dependent variables are job creation or net job creation and negative when they are job destruction. All coefficients are statistically significant at 1% level. These results suggest that higher local dividend income is associated with increased job creation and reduced job destruction, thereby contributing to net job growth. Controlling for other county-level covariates slightly increases the magnitudes of these coefficients.

The coefficients in Columns (2), (4), and (6) suggest that after controlling for other factors, a \$1 million increase in total dividend income is associated with 2.62 more job creation and 1.28 fewer job destruction, resulting in 4.06 additional jobs. To contextualize this effect, a one–standard-deviation increase in dividend income (\$141 million) corresponds to approximately 572 additional net jobs in the average county, equivalent to 1.56 times the mean and 0.3 standard deviations of net job creation.

As a comparison, regular income also exhibits a statistically significant positive association with net job creation, but the marginal effects are substantially smaller. In Column (6), a \$1 million increase in regular income is associated with only 0.38 additional jobs, around one-tenth of the effect of dividend income. This contrast in marginal effects is consistent with existing evidence that the marginal propensity to consume (MPC) out of regular income is relatively low (e.g., Jappelli and Pistaferri, 2010), while the MPC out of dividend income is considerably higher (see Table A.2 for a summary of literature). It also aligns with empirical findings that deposits respond more strongly to dividend income than to regular income (Lin, 2021).[13]

[13] While the marginal effect of regular income is smaller, its aggregate impact on employment can be larger due to scale. For example, a one–standard-deviation increase in regular income (\$9.376 billion) is associated with 3,563 additional net jobs—9.7 times the mean and 1.8 standard deviations of net job creation.

For other control variables, the effect of unrealized capital gains on job creation is positive while insignificant, as revealed by the coefficients of $Div\ Ratio \times Return$. In addition, counties with a higher population growth and unemployment rate create more jobs. The former likely reflects increased job demand in expanding regions, while the latter indicates greater labor supply in areas with slack labor markets. Regions with a larger elderly population exhibit lower rates of both job creation and destruction, resulting in no significant difference in net job creation rate.

As discussed above, the OLS estimation does not point to a casual inference. I construct a shift-share instrument, $Dividend^{Proj}/Emp$, for $Dividend/Emp$ and present the IV estimation results in Table 3. Column (1) reports the first-stage result. The coefficient of $Dividend^{Proj}/Emp$ is positive and statically significant with a t-statistic of 8.44. The F-statistic of 71.2 exceeds the rule-of-thumb threshold of 10, satisfying the relevance assumption. The point estimates of the control variables suggest that county-level dividend income is positively related to the stock market return, the level and the growth population, and other income. Furthermore, the positive association between elderly population share and dividend income supports the local dividend clientele effect: older individuals favor dividend-paying stocks for stable income (Graham and Kumar, 2006; Becker et al., 2011; Hartzmark and Solomon, 2019).

Columns (2)–(4) present the second-stage estimation results. Similar to the OLS estimation, the coefficients of *Dividends/Emp* are positive when the dependent variables are job creation or net job creation and negative when they are job destruction. The result confirms that the OLS estimation is robust and not driven by endogenous problems. The magnitudes of my IV estimates exceed their OLS counterparts. This is partly because, unlike OLS which estimates a population average treatment effect, IV estimates a local average treatment effect (LATE), which is often larger than the OLS estimate (Jiang, 2017). In my design, the IV estimate is more influenced by counties where projected and actual dividends are highly correlated, as these contribute more variation in the first-stage prediction. Untabulated results show that such counties include major corporate centers like Los Angeles (CA), Suffolk (NY), and Montgomery (MD), where large dividend-paying firms are headquartered. In these places, dividend shares are more stable for two reasons: (1) local households are more likely to hold stocks of nearby public firms, whose dividend payouts tend to be persistent; and (2) total dividend income is large, so percentage fluctuations are mechanically smaller compared to smaller counties, where portfolio rebalancing or small base effects can cause large year-over-year changes. In a result, their predicted dividend is more related to actual dividends.

To show the robustness of the IV estimation, I construct an alternative IV. This instrument builds on the dividend clientele literature, which documents that senior investors have a higher tendency to invest in dividend-paying stocks. The instrument for dividend income is constructed as the sum of projected dividends across five age brackets. The projection in each bracket uses the number of dividend filings in 2006 (the first year the IRS reports national dividends by age group) in a given county as the predetermined "share," and the national average dividends per return in that bracket as the "shift." The construction of this alternative IV projects dividends by assuming that a county has the same average dividends per return as the national value within each age group in 2006 and leaves all variation coming from national dividend trends, reflected in the age-specific national averages. Table A.4 reports the IV estimation results using this alternative shift-share instrument. All results are robust and consistent to the finding shown in Table 3.

Overall, both OLS and IV estimates show a robust positive effect of county-level corporate payouts on job creation. For other business dimensions, Table A.5 show that dividends also positively affect total wages, as well as establishment entry and exit. However, the effect on net establishment entry is positive but not statistically significant in the aggregate. When disaggregated by size, higher dividends significantly increase net entry for small establishments, but not for large ones. This result is consistent with the view that dividend income, being modest relative to regular income, is insufficient to sustain larger firms. This conclusion is further supported by evidence presented later.

A concurrent study by Müller-Dethard et al. (2025) finds a declining tendency to consume dividends and an increasing likelihood of reinvestment, due to brokerages shifting from depositing dividends into checking accounts to directing them into brokerage cash accounts. Figure A2 estimates Equation 1 using rolling three-year windows (four-year window for the final period) during 1990-2020. It shows the effect indeed decreases in 2000s but keeps persistent since then. This pattern aligns with the fact that many brokers started offering and more investors keep cash in the brokerage account in the new century (Müller-Dethard et al., 2025). Though decreasing than 1990-1999, the effect is still significant and persisist from 2000 onward.

A concurrent study by Müller-Dethard et al. (2025) documents a shift from consumption and deposit toward reinvestment of dividends, driven by brokerages routing dividends into brokerage cash accounts rather than checking accounts. Figure A2 estimates Equation 1 using rolling three-year windows (with a four-year window for the final period) from 1990 to 2020. Consistent with Müller-Dethard et al. (2025), the estimated effects decline before the Global Financial Crisis but remain positive and statistically significant thereafter. This persistence suggests the market has reached a relative equilibrium in the allocation of dividends across consumption, deposit, and reinvestment and the dividend income still plays an important role in creating jobs today.

3.2 Difference-in-differences Analysis

3.2.1 Background on 2010 and 2012 Special Dividends

In this section, I exploit a shock that affected local dividend income to further validate the main finding documented above. The Jobs and Growth Tax Relief Reconciliation Act (JGTRRA), enacted under the Bush Administration in 2003, significantly reduced the maximum tax rates on dividends (from 39.6% to 15%) and capital gains (from 20% to 15%). These tax cuts were set to expire on December 31, 2010. In late 2010, a legislative deadlock in Congress over the extension of these tax cuts led many to believe that no action would be taken and that tax rates would revert to their pre-JGTRRA levels.[14] This uncertainty was resolved on December 17, when the Tax Relief, Unemployment Insurance Reauthorization, and Job Creation Act was signed into law, granting a two-year extension of the reduced tax rates. At the end of 2012, the JGTRRA was again set to expire and the top dividend tax rate was expected to revert to 39.6%. Congress eventually passed a compromise on January 2, 2013, raising the rate slightly

[14] Hanlon and Hoopes (2014) provide details on the media coverage of the discussions surrounding the extension.

to 20%, retroactive to January 1.[15]

In anticipation of a return to higher dividend tax rates, U.S. corporations paid large amounts of special dividends in the fourth quarters of 2010 and 2012. In addition to special dividends, many firms also shifted regular dividend payments from January to December, saving shareholders an estimated $2.1 billion in total (Hanlon and Hoopes, 2014). Following Hanlon and Hoopes (2014), I define special dividends as cash dividend labeled as year-end or final, extra or special in CRSP distribution dataset (codes 1262 or 1272). Figure 2, Panels A and B plot the number and total amount of special dividends paid each quarter from 2006 to 2018 by firms with ordinary common stock (CRSP share codes 10 or 11). The dividend amount is calculated as the number of shares outstanding multiplied by dividends per share and adjusted to 2020 dollars. Panel A shows that 102 and 255 special dividends were paid in 2010Q4 and 2012Q4, respectively—approximately two and five times more than in the same quarter of other years. Panel B shows that the total amount of special dividends reached $16.4 billion in 2010Q4 and $35.4 billion in 2012Q4.

Panels C and D provide a comparison for the trend of regular dividends, defined as quarterly, monthly, semi-annual, or unspecified frequency payments (CRSP codes 1232, 1212, 1222, 1242), following Hanlon and Hoopes (2014). Panel C shows that around 250 regular dividends were shifted from January 2013 to December 2012. A smaller but similar shift occurred at the end of 2010. Panel D confirms a spike in the amount of regular dividends in 2012Q4 followed by a decline in 2013Q1, suggesting a timing shift rather than an increase in regular dividend payments.

The patterns in Figure 2 are consistent with the view that special dividends are more flexible responses to one-time shocks than regular dividends. They also help rule out the possibility that the observed changes are driven by long-term shifts in firm profitability, which could otherwise influence job creation through alternative channels.[16] Overall, firms' special dividend payments around 2010 and 2012 offer a plausibly exogenous setting to examine the effect of dividend

[15] In addition, a 3.8% surtax on net investment income, mandated by the Patient Protection and Affordable Care Act of 2010, also took effect on January 1, 2013, for certain high-income taxpayers.

[16] The shift in regular dividend payments does not substantially change the total amount paid over time; it merely accelerates the timing. Importantly, my job creation measure spans March to March, capturing both December and January. As a result, the timing shift in regular dividends does not affect the measured outcome.

income on job creation.

3.2.2 DID Design and Results

I exploit cross-sectional variation in counties' exposure to special dividends using a difference-in-differences (DID) design. The exposure measure is motivated by the local investment bias literature (e.g., Ivković and Weisbenner, 2005; Seasholes and Zhu, 2010), which documents that investors tend to overweight local public firms in their portfolios due to familiarity bias. Moreover, employees, who frequently hold equity stakes in their employers, often reside in the same county where the firm is headquartered. Consequently, the headquarters county of a public firm is likely to receive a disproportionate share of the firm's special dividend payments. Based on this reasoning, I define a treated county as one that hosted at least one public firm (CRSP share codes 10 or 11) paying a special dividend in either 2010Q4 or 2012Q4.[17]

Given the significant role public firms play in shaping local economic conditions, counties with a headquartered public firm may differ systematically from those without one, particularly in the years following the financial crisis, when public firms were expected to rebound strongly. To ensure comparability, I therefore restrict the control group to counties that have at least one public firm headquartered locally but did not receive special dividend payouts in 2010Q4 or 2012Q4.

The DID regression equation is as follows:

$$\begin{aligned} Y_{i,t} = & \sum_{k=2006,\, k\neq 2009}^{2018} \beta_k \, Payers_i \times Year_t^k + \delta_1 Firm\ Sale\ Growth_{i,t-1} + \delta_2 Firm\ Employ\ Growth_{i,t-1} \\ & + \gamma' X_{i,t} + \eta_i + \mu_{s,t} + \varepsilon_{i,t}, \end{aligned} \tag{5}$$

where $Payers_i$ indicates whether any local public firm paid special dividends in 2010Q4 or 2012Q4. $Year_t^k$ indicates year k and the reference year is 2009. The coefficients β_k estimate the differential change in the outcome variable in counties with special dividend-paying firms relative to counties without, in year k compared to the baseline year 2009, controlling for other

[17] I identify each firm's headquarters county by merging headquarters ZIP codes provided by Joshua Lee (used in Jennings, Lee, and Matsumoto (2017)) with the ZIP–county crosswalk from the U.S. Department of Housing and Urban Development.

covariates and fixed effects.

In addition to the control variables and fixed effects in Equation 1, I include two local public firm characteristics—sales growth and employment growth—to account for potential confounding from firm fundamentals. Firms not paying special dividends may be less profitable or financially unhealthier than firms did, these difference could affect future development and local labor market outcomes. Controlling firm sale growth can capture the difference in local public firm profitability. In addition, public firms may have experienced heterogeneous impacts from the Global Financial Crisis and thus followed different recovery paths. Employment growth at these firms captures their post-crisis expansion and directly influences local labor demand, making it an important control to isolate the effect of special dividends on broader job creation. If a county has multiple public firms, I compute these variables as the asset-weighted average across firms. Because these variables are based on firms' fiscal years, which may end after the calendar year, I lag the values by one year to ensure they precede the measurement of the outcome variables.

I consider two outcome variables, $Y_{i,t}$. To validate the measure of exposure, I examine the dividend growth, $\frac{\Delta Dividends_{i,t}}{Emp_{i,t}}$, measured as the annual change in dividend income scaled by the total employment. The second outcome variable is the change in job creation, $\frac{\Delta Net\ \ Job\ \ Creation_{i,t}}{Emp_{i,t-1}}$, defined as the annual change in net job creation divided by county employment. As noted ealier, job creation is measured from March in the focal year to March in the next year. Accordingly, $\frac{\Delta Net\ \ Job\ \ Creation_{i,t}}{Emp_{i,t}}$ captures the incremental net job creation from March of year t to March of year $t+1$, relative to the preceding March-to-March period.

Figure 3, Panel A, plots the average dividend growth in counties with and without special dividend payers from 2006 to 2018. Consistent with my conjecture, counties with special dividend-paying firms experienced sharper spikes in dividend growth than others in 2010 and 2012. The growth was slightly lower for counties with special dividend payers in 2011 and 2013, partially reflecting mechanical reversals due to elevated payout levels in the prior year and the intertemporal shifting of dividends (e.g., from 2013Q1 to 2012Q4). The dividend growth was parallel and close in other years, suggesting that the larger dividend growth in 2010 and 2012 in special dividend-paying counties was not driven by other unobserved shocks.

Panel B plots the DID regression coefficients from Equation 5. Consistent with the evidence in Panel A, β_{2010} and β_{2012} are positive, large in magnitude, and statistically significant, while β_{2011} and β_{2013} are negative but smaller in magnitude. The 2008 coefficient is also positive and statistically significant, though modest in size. Pre-treatment coefficients for other years are close to zero and insignificant, supporting the parallel trends assumption. From 2014 onward, the estimates remain mostly positive and significant but are notably smaller, suggesting a persistent yet weaker divergence in dividend growth compared with 2009. Together, Panels A and B indicate that the large special dividends in 2010 and 2012 led to sharp but short-lived surges in dividend income in counties with special dividend-paying firms.

With the preceding evidence on dividend income, I now examine whether job creation also differs across counties with and without special dividend payers. Panel C of Figure 3 plots the average change in net job creation from 2006 to 2018. Consistent with the earlier pattern in Panel A, counties with special dividend payers experienced higher net job creation growth in 2010–2015, except for 2013. The most noticeable change was in 2010 and 2012, the years when the special dividends were paid. Panel D plots the corresponding DID regression coefficients. Relative to 2009, treated counties saw statistically significant increases in job creation in most years from 2010 to 2015, consistent with the patterns in Panel C.

The short lag between the 2010Q4 special dividends and the observed rise in job creation by March 2011 aligns with a rapid consumption response to dividend income (Baker et al., 2007; Bräuer et al., 2022). For example, Bräuer et al. (2022) show that household spending rises sharply within a few weeks of dividend receipt. The fourth-quarter timing also overlaps with the holiday season, when consumption typically surges, potentially boosting local labor demand. The effects observed in 2014–2015 likely reflect a delayed response to the 2012 special dividend. The absence of effects after 2016 supports the notion that these patterns were not driven by persistent structural differences between payer and non-payer counties. Overall, Panels C and D indicate that special dividend payouts led to temporary but meaningful increases in job creation.

In sum, the analyses in this section leverage a surge in special dividends induced by exogenous uncertainty about potential tax hikes. In this setting, where shocks to local dividend payments are unrelated to local firms' profitability, local economic conditions, and other predictors of local job creation, I continue to find that dividend income positively affects local job creation. This evidence supports dividend payments as the causal channel for the documented variation in job creation across counties.

4 Channel Analyses

4.1 Consumption Channel

Prior research has extensively documented the consumption effect of dividend income using household-level data, such as Baker et al. (2007); Di Maggio et al. (2020); Bräuer et al. (2022). For my interest, this subsection investigates the potential aggregate implications at the county level. This aggregate analysis complements household-level work by capturing aggregate demand shifts that may not be visible in household data.

The literature (e.g., Mian and Sufi, 2014; Giroud and Mueller, 2017; Chodorow-Reich et al., 2021) shows that sales and employment in nontradable sectors (NAICS 44-45 and 72, e.g., restaurants, retail stores, and hotels) are closely tied to local household demand, whereas tradable sectors (NAICS 11, 21, or 31-33, e.g., agriculture, mining, and manufacturing) is more affected by national or global demand. If dividend income boosts county-level consumption, we should observe a positive relationship between dividend income and sales in local nontradable sectors.

Following Gilje (2019), I obtain county-level sales by sectors data from the Census Bureau's quinquennial Economic Census Survey conducted in years in 1997, 2002, 2007, 2012, 2017, and 2022. The Economic Census provides employment, payroll, and measure of output, and other information on county-level business establishments across sectors and geographic areas. The key advantage for using the Economic Census sale data is that it provides county-level coverage, while the BEA consumption data is only available at the state level.

The Census Economic Survey excludes agriculture (NAICS 11), manufacturing (NAICS 31-33) and public administration (NAICS 92) sectors. Sales data for mining (NAICS 21), construction (NAICS 23), and firm management (NAICS 55) sectors are only available for limited counties in 2007 and 2012, so I exclude these sectors. The final data do not cover sales in tradable sectors but include all nontradable sectors and most other industries. Because Census Bureau survey data are typically collected one year before the reporting year, I merge sales with county variables lagged by one year.

Table 4 reports regressions of log sales per employment on dividend income per employment and controls. Columns (1) and (2) focus on two nontradable sectors: retail trade (NAICS 44–45) and accommodation and food services (NAICS 72). Column (3) presents results for all other sectors, while Column (4) includes all sectors covered in the Census Economic Survey. The coefficient on *Dividends/Emp* is positive and statistically significant for sales in both nontradable sectors and for total sales across all sectors. However, dividend income does not affect sales in other sectors in the OLS estimation. The IV estimation shows a positive and statistically significant across all columns. The magnitudes are the largest in the retail sale sector in both the OLS and IV estimations. Results in Table 4 aligns with the fact that revenues in nontrable sectors are more directly tied to retail consumers than other sectors.

Mian and Sufi (2014) and Chodorow-Reich et al. (2021) show that shocks to household consumption affect employment in nontradable sectors, but not in tradable sectors. While Table 4 supports the consumption channel, it does not allow a direct comparison between tradable and nontradable sectors due to data limitations. To address this, I examine whether the effect of dividend income on job creation differs across sectors. If the consumption channel is the primary mechanism, the positive impact should be concentrated in nontradable sectors. I re-estimate Equation 1 separately for nontradable, tradable, and other sectors, using sector-level job creation aggregated at the county level. Results are presented in Table 5. "Others" sectors include all those excluding the nontradable and tradable sectors.[18]

The estimates in Table 5 show that dividend income positively affects net job creation across all sector types. As plotted in Figure 4, the effect is strongest in "Others" sectors, followed by nontradable and then tradable sectors. While dividend income primarily boosts

[18] As a comparison, "Others" sectors in Table 5 include all sectors under "Other Sectors" in Table 4 as well as those excluded from the Census Economic Survey.

sales in nontradable sectors, the employment effect is not concentrated there, suggesting that the consumption channel is not the primary—or at least not the only—mechanism at work.[19]

4.2 Deposit Channel

4.2.1 Dividends and Deposits

This section examines the relation between county-level dividend income and bank deposits. Specifically, I estimate Equation 1 by replacing the dependent variable with the deposit growth rate. The FDIC's Summary of Deposits (SOD) dataset reports branch-level deposits as of June 30 each year since 1994. To calculate county-level deposits in calendar year t, I first aggregate all branch-level deposits within the county and then take the average of deposits reported on June 30 of years t and $t{+}1$.

Table 6 reports the estimation results. Since the dependent variable is related to deposits rather than employment, I adjust the scaling accordingly. Columns (1) and (3) scale the change in deposits and dividends by lagged deposits, so the dependent variable $\frac{\Delta Deposit_{i,t}}{Deposit_{i,t-1}}$ represents the deposit growth rate. Columns (2) and (4) scale both the change in deposits and dividends by population to measure changes in deposits and dividend income on a per capita basis.

Table 6 shows consistent evidence that dividend income flows into banks as increased deposits. For example, the OLS estimates suggest that \$0.12–0.21 of every \$1 in dividends are deposited. These findings align with Lin (2021), supporting the view that dividend income contributes to local deposit growth.

4.2.2 Dividends, Bank Lending, and Job Creation

For increased deposits to translate into greater bank lending and subsequently affect local employment, two conditions must hold: (1) local firms need to rely on banks for funding; and (2) banks are unlikely to draw capital from other regions to supply credit (Gilje et al., 2016). Two stylized facts support the plausibility of these conditions. First, firms with fewer than 100

[19]If consumption were the primary channel, the dividend clientele theory (Graham and Kumar, 2006) would predict a stronger effect in counties with a larger elderly population. However, untabulated results show that the share of residents aged 65 and above does not significantly moderate the main effect.

employees accounted for 98.1% of all firms in 2019.[20] Given that small firms primarily rely on banks for financing (Petersen and Rajan, 1994; Chodorow-Reich, 2014), the increased deposits can play an important role as fueling credit supply. Second, more than 97% are community banks, which primarily fund local loans with local deposits (Hanauer, Lytle, Summers, Ziadeh et al., 2021). Given these patterns, I predict that dividend income are positively associated with local bank lending. This section first examines the effect of dividends on small business loans, then conducts cross-sectional analyses based on each condition above.

According to the Small Business & Entrepreneurship Council, small businesses accounted for two-thirds of net new jobs between 2000 and 2019.[21] Since most firms are small and tend to borrow modest amounts, I focus on small business lending (SBL). Specifically, I use loans of $1 million or less from the Community Reinvestment Act (CRA) dataset.[22] In addition to the overall small business lending in a county, the CRA also provides loan data by borrower revenue and loan size, allowing me to test heterogeneous effects. I classify firms as small (revenue below $1 million) or large (revenue above $1 million), and loans as small (loans smaller than $100,000), medium (loans between $100,000 and $250,000), or large (loans between $250,000 and $1 million). The theory under the first condition implies stronger effects for small firms and small loans, which are more likely tied to constrained borrowers.

Table 7 presents the regression results where I regress the loan amount per employment on dividends per employment and controls. Panels A and B show OLS and IV estimates, respectively. Column (1) considers total SBL. Columns (2) and (3) disaggregate lending by borrower size, while Columns (4)–(6) break down lending by loan size. In each column, the dependent variable is the total loan amount in the relevant category scaled by total employment.

Column (1) shows a positive and statistically significant association between dividend income and small business lending. Both dividends and loan amount are in thousand dollars. The OLS coefficient indicates that $1,000 dollar dividends results in $653 dollar small business loans. For the sub-sample tests, as visualized in Figure 5, the effect is more pronounced for

[20]Data source: the Census Bureau data https://sbecouncil.org/about-us/facts-and-data/.

[21]Source: https://sbecouncil.org/about-us/facts-and-data/.

[22]The CRA dataset reports the aggregate number and amount of small business loans originated or purchased during the reporting year at the census tract level. I aggregate it to the county level. See Bord, Ivashina, and Taliaferro (2021) for a detailed discussion of the CRA data.

small firms (\$425 vs. \$227 for large firms) and for small loans (\$404 vs. \$49 and \$199 for medium and large loans, respectively). These patterns are consistent with prior evidence that small firms and borrowers seeking small loans are bank-dependent and thus sensitive to credit supply shocks (Petersen and Rajan, 1994; Chodorow-Reich, 2014).

For the first condition that local firms need to rely on banks for funding, given that small and young firms are generally more reliant on bank financing, I expect the employment effect of dividend income to be stronger for these firms. To test this hypothesis, I conduct cross-sectional analyses by establishment size and age. The results are reported in Table 8. Panel A estimates the effect of dividend income on net job creation by establishments with 1–19, 20–499, and 500 or more employees. Panel B estimates the effect of dividend income on net job creation by establishments that are 0, 1–5, 6–10, and more than 10 years old, respectively. Consistent with my prediction and the findings in Table 7, the results suggest that dividend income has the strongest effect on job creation among the youngest and smallest firms, as plotted in Figure 6.

To provide more direct evidence on the deposit channel, I further conduct subsample analyses on sectors' reliance on bank financing for expansion. Following Doerr et al. (2024), I measure sectors' bank dependence using the fraction of firms reporting bank loans for startup or expansion based on the 2007 Survey of Business Owners (SBO). The SBO collects information on business owner and business characteristics for all nonfarm businesses filing IRS tax forms with more than \$1,000 in receipts. There are 2.17 million observations about business owner information in the 2007 survey. Since the SBO data covers all non-farm businesses, it provides a comprehensive view of how businesses across sectors rely on bank loans.[23] A firm is classified as bank-dependent if it answers "Yes" to either the question `"Source of Startup Capital: Bank Loan"` or `"Source of Expansion Capital: Bank Loan."` I then calculate the fraction of bank-dependent firms within each sector. A sector is defined as high bank-dependent if this fraction falls in the top half of all sectors. Table A.6 lists the share of bank loan usages and the classification for each two-digit NAICS sector.

Table 9 presents the cross-sectional results from estimating Equation 1 by sectors' bank dependence. The coefficients on *Dividends/Emp* are positive and statistically significant in

[23] See https://www.census.gov/econ/overview/mu0200.html for detailed documentation on the SBO data.

both high- and low-dependent sectors. The high-dependent sector has a larger magnitude than the low-dependent sector. Figure 7 visualizes the comparison. This pattern aligns with the earlier finding that dividend effects are stronger for small and young firms. Notably, Table A.6 shows that all three tradable sectors are classified as highly bank-dependent. Taken together, the stronger employment response in high-dependence sectors suggests that the consumption channel is unlikely to be the dominant mechanism. Another common measure of a sector's bank dependence in the literature is the external finance requirement of public firms (e.g., Rajan, 1998). However, the SBO data is more appropriate for my research question, as most businesses are much smaller than public firms and may rely differently on bank loans. That being said, Table A.7 shows that the result is robust to this alternative approach.

Regarding the second condition regarding banks' ability to redeploy capital across regions, I examine whether the employment effect of dividend income is stronger in counties where banks are more likely to lend locally. Following Gilje (2019), who find that areas dominated by small banks benefit more from local credit expansions, I hypothesize that the effect of dividends on employment is more pronounced in counties with a higher share of small or regional banks, which are more sensitive to local deposit inflows (Gilje, 2019; d'Avernas, Eisfeldt, Huang, Stanton, and Wallace, 2023).

Panel A of Table 10 focuses on bank size. Following Gilje (2019), I define a small bank as one with total assets below \$500 million (in 2020 dollars).[24] For each county-year, I calculate the deposit-weighted share of branches operated by small banks and split counties into *High Share* and *Low Share* groups based on the annual median. I then estimate Equation 1 separately for each group. The results are presented in Panel A of Table 10. The results show that dividend income positively affects job creation in both groups, with substantially larger magnitudes in counties with a higher small-bank presence. Figure 8 plots the estimated coefficients to facilitate comparison.

Panel B considers the geographic reach of local banks. I define a bank as a regional bank if it operates only within a single county. All increased deposits at such banks are assumed to be lent locally. If a county is dominated by these banks, the effect of dividends on local job

[24]The results are robust to alternative thresholds of \$100 million, \$200 million, and \$1 billion.

creation should be stronger than in counties where banks can deploy deposits across regions. Using the same deposit-weighted share classification approach, I find that the employment effect of dividend income is again stronger in counties dominated by regional banks. Taken together, Table 10 provides strong support for the second condition: the stimulative effect of increased deposits is amplified when local banks serve local borrowers.

To sum up, this section suggests that dividend income boosts local employment primarily by expanding credit through local banks. This effect is primarily concentrated among small and young establishments and is stronger for bank-dependent firms and in counties dominated by small and regional banks.

5 Robustness Checks

This section serves as robustness checks for possible confounding factors that affects my findings. Table 11, Panels A and B present the OLS and IV estimation results of including additional control variables into Equation 1.

Dividend income may proxy for broader county-level economic conditions. For example, as a county develops, households may become more optimistic and increase their stock market participation, leading to higher dividend income. To mitigate this concern, Column (1) includes the log and the growth rate of county-level GDP to account for a county's economic condition and growth, respectively. Since the GDP data begin in 2001, and one year is needed to compute growth, the sample period starts in 2002.

Moreover, it is well established that the regional business environment, such as skilled labor and innovation networks, as seen in places like Silicon Valley, plays a critical role in fostering entrepreneurship. In Column (2), I control for county-level entrepreneurial quality using a measure developed by Fazio, Stern, Guzman, Liu, and Andrews (2019) and Guzman and Stern (2020). This index measures the average quality (*i.e.,* the probability of achieving a growth outcome) of all firms in a county.

The observed increase in small business lending, which in turn spurs the job creation, may primarily reflect broader credit supply shocks, such as rising local bank deposits by other factors, regulatory easing, or improved funding conditions in the banking sector. To account for this possibility, I construct a credit supply shock for small business lending measure following Greenstone, Mas, and Nguyen (2020). Specifically, I regress the annual change in the log amount of small business lending, $\Delta Ln(Q_{ij})$, on the bank (d_i) and county (d_j) fixed effects for each bank-county observation each year using the following equation:

$$\Delta \ln(Q_{ij}) = d_i + s_j + e_{ij}. \tag{6}$$

I weight this equation by each bank's lending share in county j in year $t-1$. The bank fixed effects, s_j, capture the component of the change in bank j's small business lending in county i that is explained by the bank's credit supply, orthogonal to county-specific factors. I further re-center s_j to have a mean of zero each year.[25] Lastly, I calculate the county-level credit supply shock, *Credit Supply*, as the lending-weighted sum of s_j for banks operating in the county. Column (3) reports the result including *Credit Supply*.

Education also can be a confounding factor, as it relates to both household stock market participation (Campbell, 2006) and entrepreneurship (Robinson and Sexton, 1994). I measure a county's education level with the percentage of individuals aged 25 or older with a bachelor's degree and include it in Column (4).

Prior literature documents that house prices play an important role in stimulating local business activity by influencing both household consumption incentives (Mian, Rao, and Sufi, 2013) and entrepreneurs' collateral values for obtaining business loans (Adelino, Schoar, and Severino, 2015). In the mean time, changes in house prices affect household investment decisions (Chetty, Sándor, and Szeidl, 2017). To account for the effect of house price change, I calculate the county-level house price growth rate, *House Price Growth*, using the House Price Index data compiled by the Federal Housing Finance Agency.

As discussed earlier, local investment bias (Ivković and Weisbenner, 2005; Seasholes and Zhu, 2010) and the presence of local workers lead households to hold a disproportionately large share of local public firms. This fact raises a concern that the relationship between

[25]This adjustment ensures that the measure captures differential credit supply shocks across banks rather than aggregate shifts in credit availability across the entire banking system over years.

dividend income and job creation in counties with dividend-paying firms may primarily reflect the performance of these firms. For example, a growing public firm with rising profitability may simultaneously increase dividend payouts and hire more workers. In such cases, the positive association between dividend income and job creation may mainly capture the expansion of public firms rather than a direct wealth effect.

Moreover, the presence of a public firm can significantly influence the local labor market. Even if the firm does not pay dividends, it may still affect local stock market participation and thus local dividend income. To address these concerns, Column (6) includes an indicator for whether a county hosts at least one public firm. Columns (7) and (8) further restrict the sample to counties with public firms and control for the sales and employment growth of those firms, respectively.

All coefficients of *Dividends/Emp* are positive and statistically significant. The results suggest that my finding is not driven by confounding omitted variables.

6 Conclusion

Net corporate payouts by U.S. public corporations surged by over 500% between 1990 and 2020, raising ongoing debate on their real effect on the economy. While critics argue that rising payouts constrain investment and exacerbate inequality, others contend that corporate payouts can channel capitals from mature firms to growing firms and thus stimulate growth. This paper contributes to this debate by examining how dividend income affects local employment outcomes.

Leveraging a county-level measure of dividend income, a shift-share instrument based on plausibly exogenous variation in public firms' payouts, and a difference-in-differences design exploiting a surge in special dividend payments driven by dividend tax changes, I find that increases in household dividend income lead to significant growth in local job creation—particularly among small and young firms. The paper identifies two transmission channels: consumption and deposits. On the one hand, households spend dividend gains, boosting demand in nontradable sectors. On the other hand, households deposit dividend income into banks, increasing local credit supply. This, in turn, facilitates small business lending and supports job growth in bank-dependent sectors.

Overall, this paper shows that corporate payouts from large and mature firms can flow to small enterprises through shareholders' direct consumption or the banking system. This finding has significant policy implications, particularly given the recent introduction of a 1% excise tax on share repurchases under the Inflation Reduction Act of 2022, with ongoing discussions to increase this rate to 4%. My finding highlights an underexplored downside of restricting corporate payouts, which will disrupt the efficient reallocation of capital from mature firms, which often have limited investment opportunities, to the broader economy, where the capital could be more productively employed.

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Figure 1: Payouts Trend from 1990 to 2020

This figure shows the payouts trend from 1990 to 2020. *Compustat dividends* plots the aggregate cash dividends (item *DVT*) distributed by all Compustat firms. *Compustat net repurchase* plots the aggregate repurchase minus issuance of stock (item *SSTK*) by all Compustat firms. Repurchases are calculated as the purchase of common and preferred stock (item *PRSTKC*) minus any reduction in the value of preferred stock. Following Kahle and Stulz (2021), I measure the value of preferred stock as the redemption value (item *PSTKRV*), liquidating (item *PSTKL*), or par value (item *PSTK*), depending on availability. *Compustat net payouts* plots the sum of dividends and net payouts by all Compustat firms. *IRS dividends* plots the aggregate county-level ordinary dividends reported to the IRS. All dollar values are adjusted for inflation to 2020 dollars.

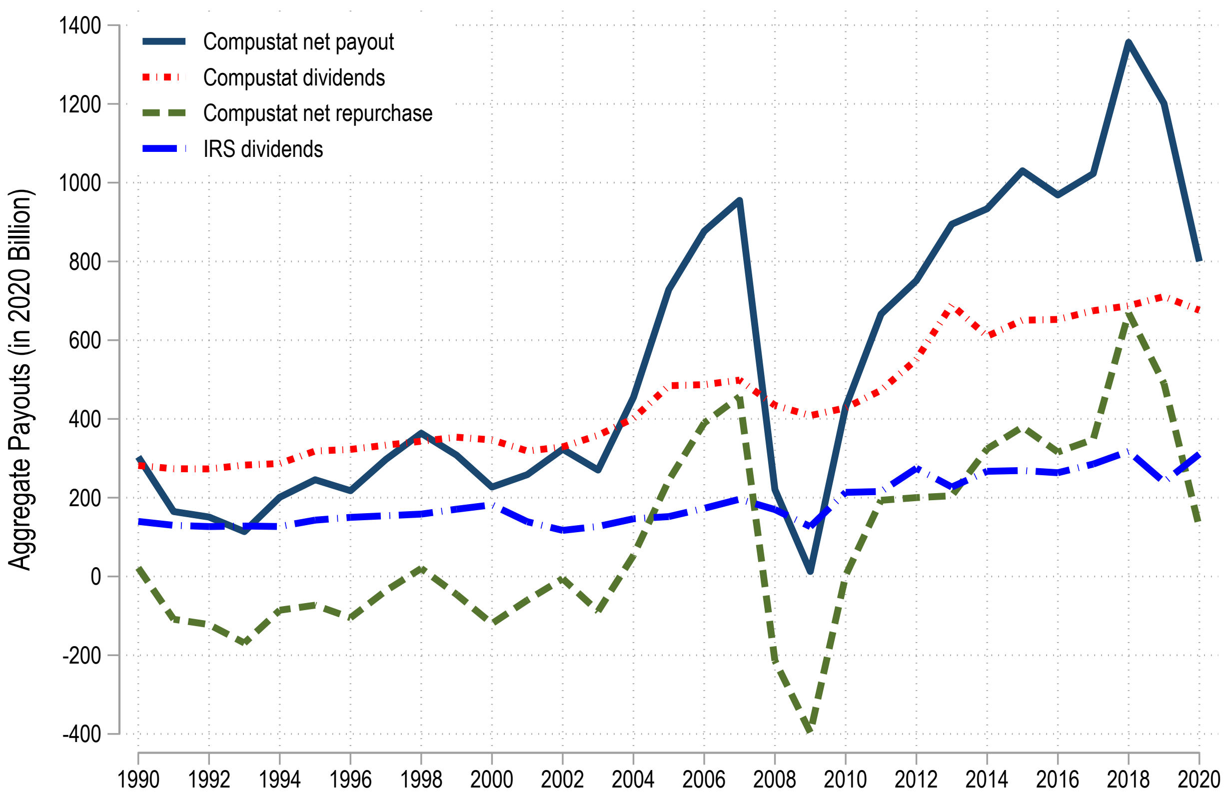
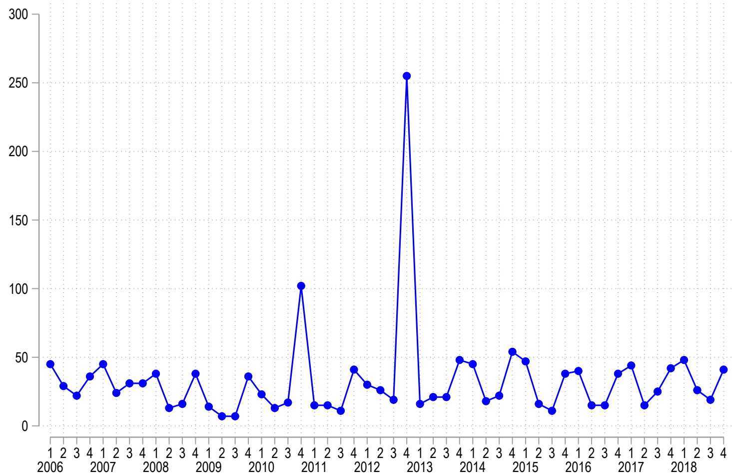


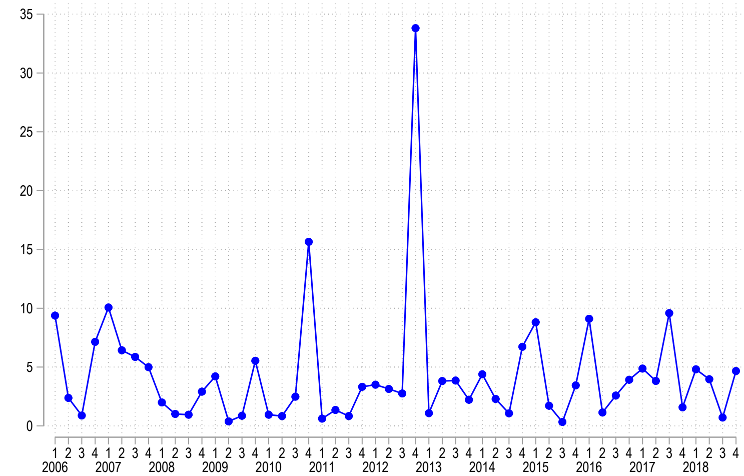
Figure 2: Special and Regular Dividends During 2006-2018

The figure plots the number and amount of special and regular dividends each quarter from 2006 to 2018. Special dividends are identified using CRSP distribution codes 1262 and 1272–cash dividend paid at the year-end or final extra or special dividend). Regular dividends are identified as those with CRSP distribution codes 1232, 1212, 1222, or 1242–cash dividends paid either quarterly, monthly, semi-annually, or with unspecified frequency. The sample includes firms with ordinary common stock, defined by CRSP share codes 10 or 11. The total amount of dividends is in billions of 2020 dollars.

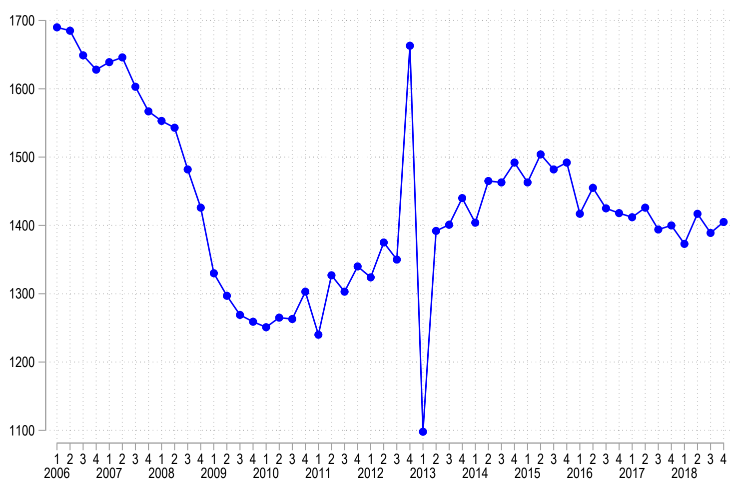
Panel A: The number of special dividends



Panel B: The amount of special dividends (billions)



Panel C: The number of regular dividends



Panel D: The amount of regular dividends (billions)

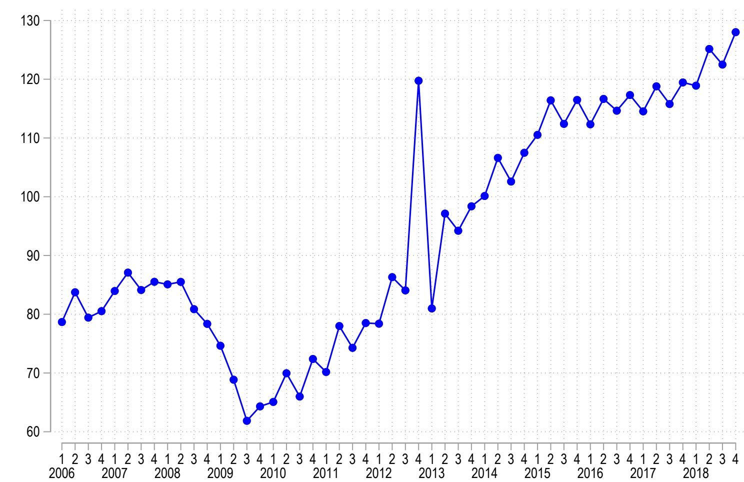


Figure 3: The Effect of Corporate Special Dividends on Job Creation

This figure examines the effect of dividend income on job creation around the 2010 and 2012 special dividends. Special dividends are identified as those with CRSP distribution codes 1262 (U.S. cash dividend, year-end or final, taxable at the dividend rate) and 1272 (U.S. cash dividend, extra or special, taxable at the dividend rate). These analyses focus on counties with at least one public firm (CRSP share codes 10 or 11) headquartered locally. Counties where a public firm paid special dividends in either 2010Q4 or 2012Q4 are defined as special-dividend payers ($Payers = 1$). All other counties with a public firm headquarters are classified as special-dividend non-payers ($Payers = 0$). Panel A plots the average dividend growth in special-dividend payers and non-payers. The dividend growth, $\frac{\Delta Dividends_{i,t}}{Dividends_{i,t-1}}$, is calculated as the change in dividend income divided by the lagged dividend income. Panel B plots the coefficients of interactions, β_k, from the following regression: $\frac{\Delta Dividends_{i,t}}{Emp_{i,t-1}} = \sum_{k=2006,k\neq 2009}^{k=2018} \beta_k Payers_i \times Year_t^k + \delta_1 Firm\ Sale\ Growth_{i,t-1} + \delta_2 Firm\ Employ\ Growth_{i,t-1} + \gamma' X_{i,t} + \eta_i + \mu_{s,t} + \varepsilon_{i,t}$, where $Year_t^k$ indicates year k and the reference year is 2009. $Firm\ Sale\ Growth_{i,t-1}$ and $Firm\ Employ\ Growth_{i,t-1}$ are the asset-weighted sale growth rate and employment growth rate of local public firms, respectively. $X_{i,t}$ include the same control variables are the same in Table 2. County and state×year fixed effects are included. Standard errors are clustered at the county level. The bars represent 95% confidence intervals of the coefficients β_k. Panel C plots the average change in net job creation, $\frac{\Delta Net\ Job\ Creation_{i,t}}{Emp_{i,t-1}}$, defined as the change in net job creation from year t-1 to year t divided by the number of employment in t-1, in special-dividend payers and non-payers. Panel D replicates the specification in Panel B using $\frac{\Delta Net\ Job\ Creation_{i,t}}{Emp_{i,t-1}}$ as the dependent variable and plots the coefficients β_k.

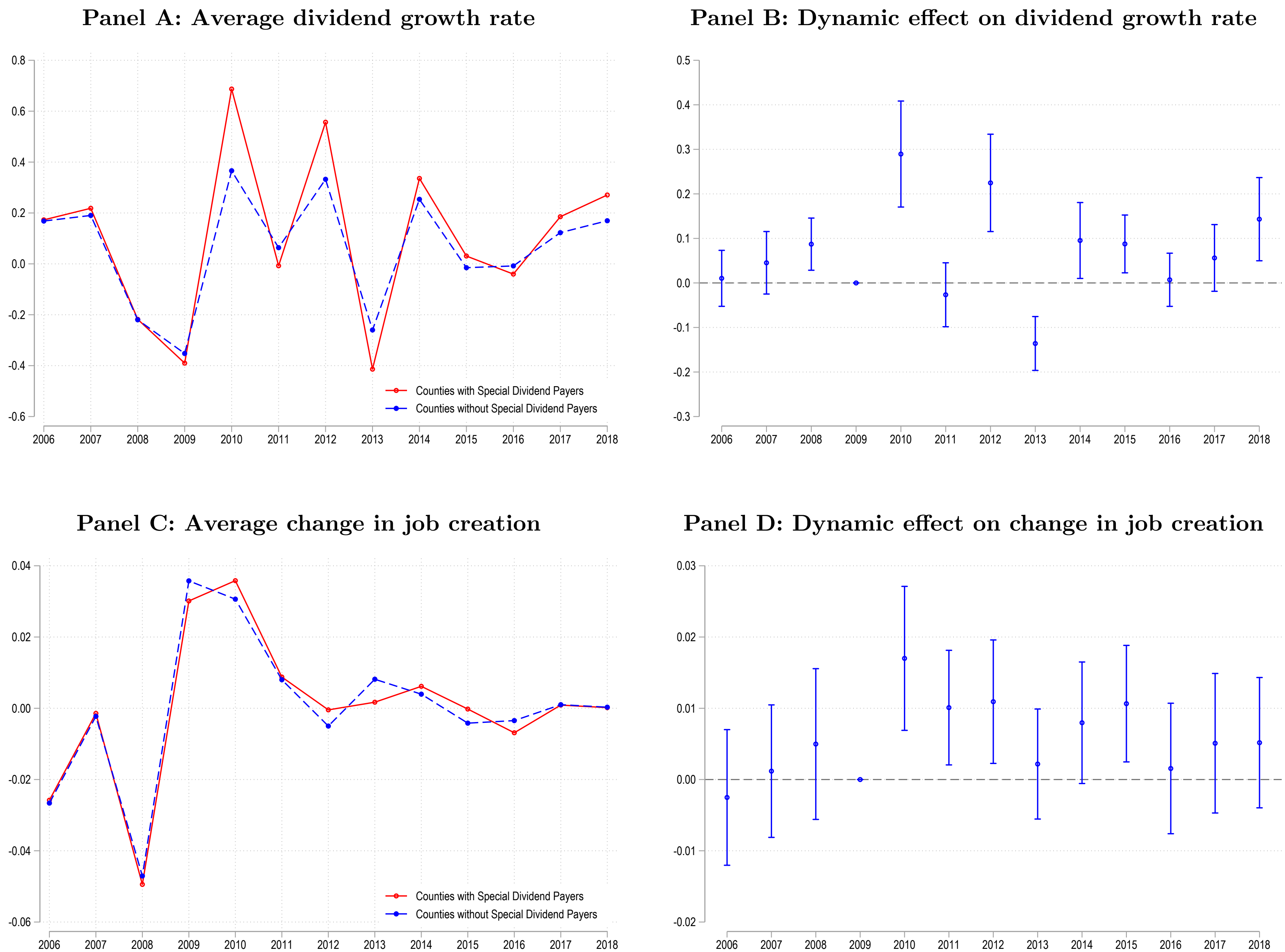

Panel A: Average dividend growth rate
Counties with Special Dividend Payers
Counties without Special Dividend Payers
Panel B: Dynamic effect on dividend growth rate
Panel C: Average change in job creation
Counties with Special Dividend Payers
Counties without Special Dividend Payers
Panel D: Dynamic effect on change in job creation
2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018

Figure 4: Cross-Sectional Analysis by Tradable, Nontradable, and Other Sectors

This figure plots the coefficients of $\frac{Dividends_{i,t}}{Emp_{i,t}}$ from the regression $\frac{Net\ Job\ Creation_{i,t+1}}{Emp_{i,t}} = \beta\frac{Dividends_{i,t}}{Emp_{i,t}} + \gamma' X_{i,t} + \eta_i + \mu_{s,t} + \epsilon_{i,t}$ in tradable, non-tradable, and other sectors. The regression results are shown in Table 5. The dependent variable is net job creation in different sectors, scaled by total employment. *Tradable* sectors include sectors with NAICS codes of 11, 21, and 31-33. *Nontradable* sectors include sectors with NAICS codes of 44-45 and 72. *Others* include all other sectors. *Dividends/Emp* is dividend income divided by total employment. The instrument, $Dividends^{Proj}/Emp$, is constructed as the product of a county's 1989 dividend share and aggregate dividends across all other counties in the same year, scaled by total employment. The blue bars plot the 95% confidence intervals of β.

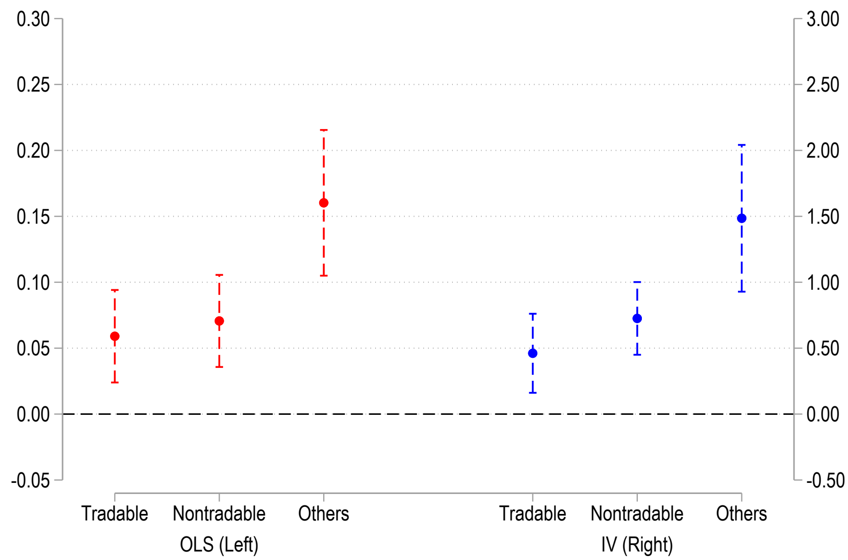
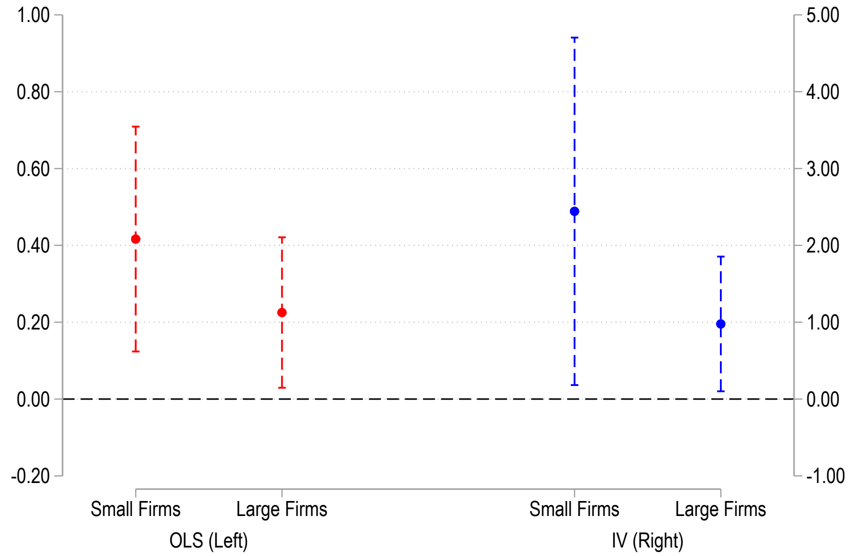


Figure 5: The Effect of Dividends on Small Business Lending

This figure plots the coefficients of $\frac{Dividends_{i,t}}{Emp_{i,t}}$ from the regression $\frac{SBL_{i,t}}{Emp_{i,t}} = \beta \frac{Dividends_{i,t}}{Emp_{i,t}} + \gamma' X_{i,t} + \eta_i + \mu_{s,t} + \epsilon_{i,t}$ by different borrower size (Panel A) and loan size (Panel B). The regression results are shown in Table 7. In Panel A, the dependent variable is the total amount of small business lending to establishments with revenues below \$1 million ("*Small Firms*") and above \$1 million ("*Large Firms*") scaled by total employment, respectively. In Panel B, the dependent variable is the total amount of small business lending to establishments with loan size under \$100,000 ("*Small Loans*"), between \$100,000 and \$250,000 ("*Large Loans*"), and between \$250,000 and \$1 million ("*Large Loans*") scaled by total employment, respectively. *Dividends/Emp* is dividend income divided by total employment. The instrument, $Dividends^{Proj}/Emp$, is constructed as the product of a county's 1989 dividend share and aggregate dividends across all other counties in the same year, scaled by total employment. The blue bars plot the 95% confidence intervals of β.

Panel A: Borrower Size



Panel B: Loan Size

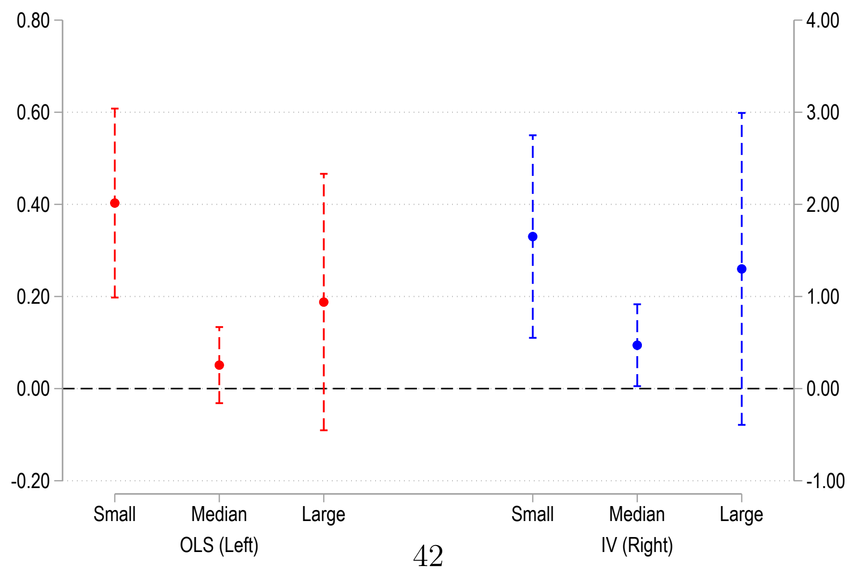
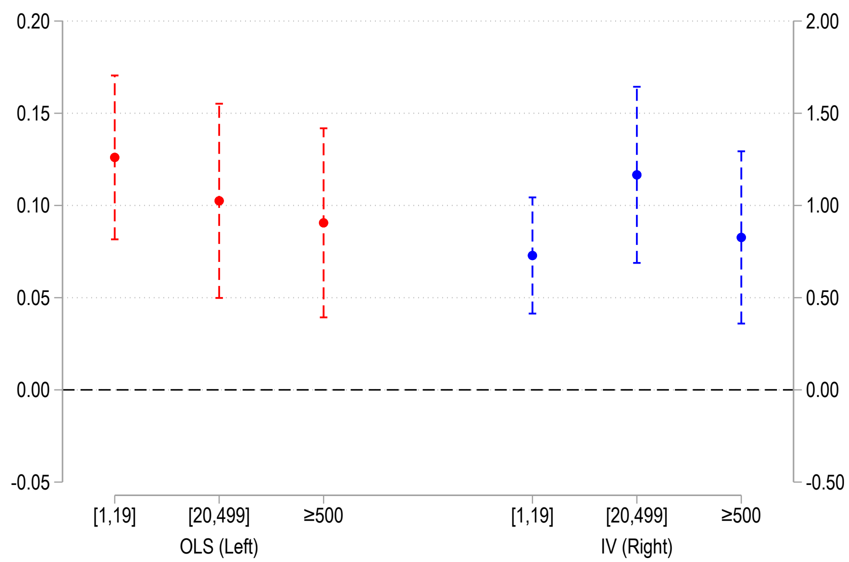


Figure 6: Cross-Sectional Analysis by Establishment Size and Age

This figure plots the coefficients of $\frac{Dividends_{i,t}}{Emp_{i,t}}$ from the regression $\frac{Net\ Job\ Creation_{i,t+1}}{Emp_{i,t}} = \beta\frac{Dividends_{i,t}}{Emp_{i,t}} + \gamma' X_{i,t} + \eta_i + \mu_{s,t} + \epsilon_{i,t}$ by establishments with different size ranges (Panel A) and different age ranges (Panel B). The regression results are shown in Table 8. Panel A reports results by establishment size. The dependent variable is net job creation by establishments with different employee ranges, scaled by total employment. "[1,19]", "[20,499]", and "≥500" represent establishments with 1–19, 20–499, and 500 or more employees, respectively. Panel B reports results by establishment age. The dependent variable is net job creation by establishments with different age ranges, scaled by total employment. "0", "[1,5]", "[6,10]", and "≥10" indicate establishments that are 0, 1–5, 6–10, and more than 10 years old, respectively. *Dividends/Emp* is dividend income divided by total employment. The instrument, $Dividends^{Proj}/Emp$, is constructed as the product of a county's 1989 dividend share and aggregate dividends across all other counties in the same year, scaled by total employment. The blue bars plot the 95% confidence intervals of β.

Panel A: Establishment Size



Panel B: Establishment Age

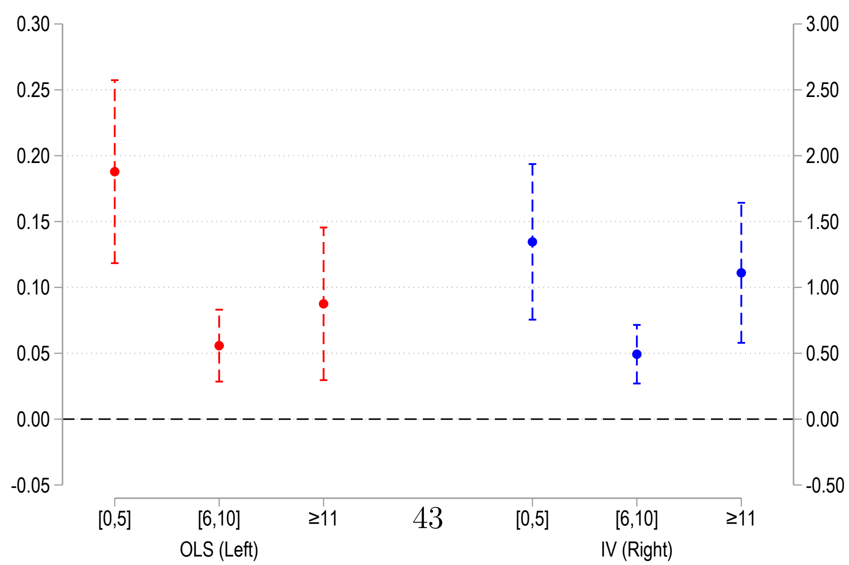


Figure 7: Cross-Sectional Analysis by Sectors' Bank Dependence

This figure plots the coefficients of $\frac{Dividends_{i,t}}{Emp_{i,t}}$ from the regression $\frac{SBL_{i,t}}{Emp_{i,t}} = \beta\frac{Dividends_{i,t}}{Emp_{i,t}} + \gamma' X_{i,t} + \eta_i + \mu_{s,t} + \epsilon_{i,t}$ in sectors with different bank dependence. The regression results are shown in Table 9. The dependent variable is net job creation in different sectors, scaled by total employment. "*Low*" and "*High*" indicates sectors in the bottom and top half of a sector's bank dependence, respectively. A sector's bank dependence is measured as the fraction of firms within that sector that used bank loans to start or expand their businesses, based on the 2007 Survey of Business Owners. Table A.6 reports the fraction of bank loan usages and the classification for each two-digit NAICS sector. *Dividends/Emp* is dividend income divided by total employment. The instrument, $Dividends^{Proj}/Emp$, is constructed as the product of a county's 1989 dividend share and aggregate dividends across all other counties in the same year, scaled by total employment. Control variables from Table 2 are included. All variables are winsorized at the 1st and 99th percentiles. The blue bars plot the 95% confidence intervals of β.

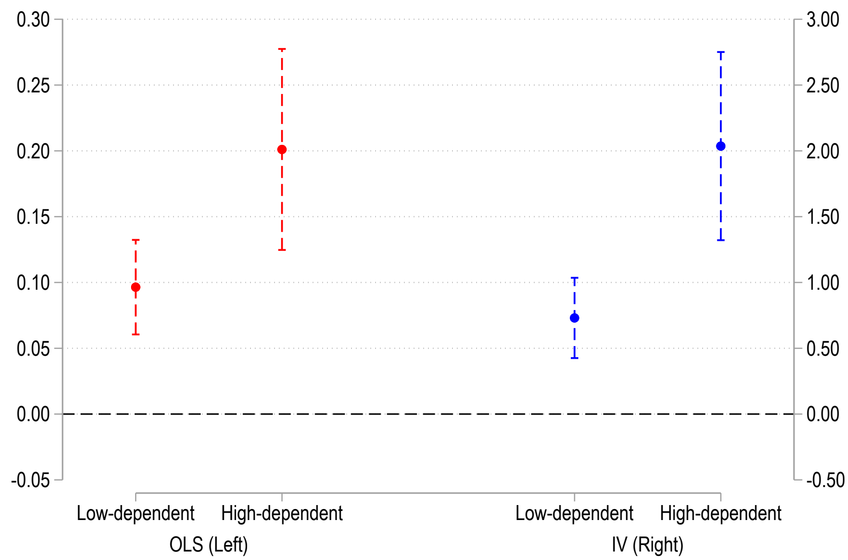
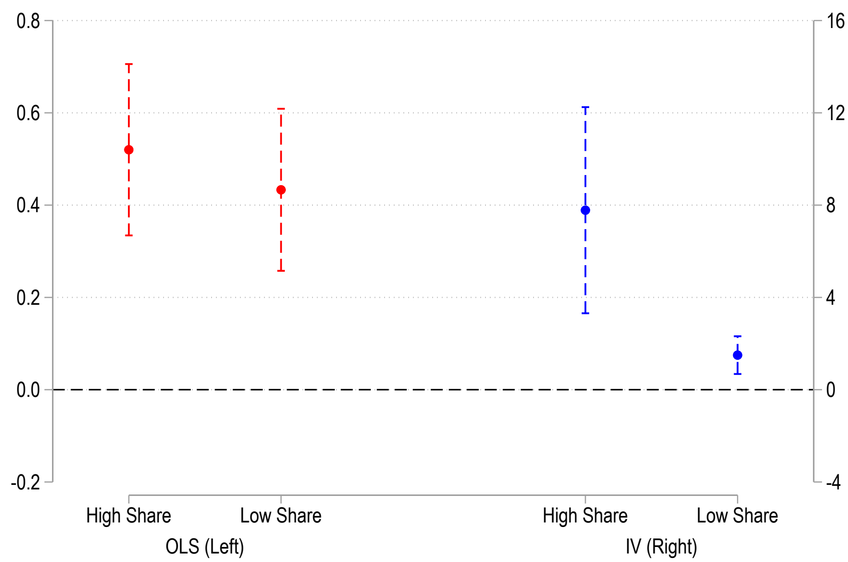


Figure 8: Cross-Sectional Analysis by Counties' Small and Regional Bank Dominance

This figure plots the coefficients of $\frac{Dividends_{i,t}}{Emp_{i,t}}$ from the regression $\frac{SBL_{i,t}}{Emp_{i,t}} = \beta \frac{Dividends_{i,t}}{Emp_{i,t}} + \gamma' X_{i,t} + \eta_i + \mu_{s,t} + \epsilon_{i,t}$ in counties with different share of small (Panel A) and regional banks (Panel B). The regression results are shown in Table 10. The dependent variable is the net job creation in counties with different small bank share (Panel A) and regional bank share (Panel B), scaled by total employment. A county's small bank share is the deposit-weighted share of branches operated by small banks (banks with total assets below $500 million). A county's regional bank share is the deposit-weighted share of branches operated by regional banks (banks only operate in a single county). "*High Share*" and "*Low Share*" are classified based on the median of the shares each year. *Dividends/Emp* is dividend income divided by total employment. The instrument, $Dividends^{Proj}/Emp$, is constructed as the product of a county's 1989 dividend share and aggregate dividends across all other counties in the same year, scaled by total employment. Control variables from Table 2 are included. All variables are winsorized at the 1st and 99th percentiles. The blue bars plot the 95% confidence intervals of β.

Panel A: The Share of Small Banks



Panel B: The Share of Local Banks

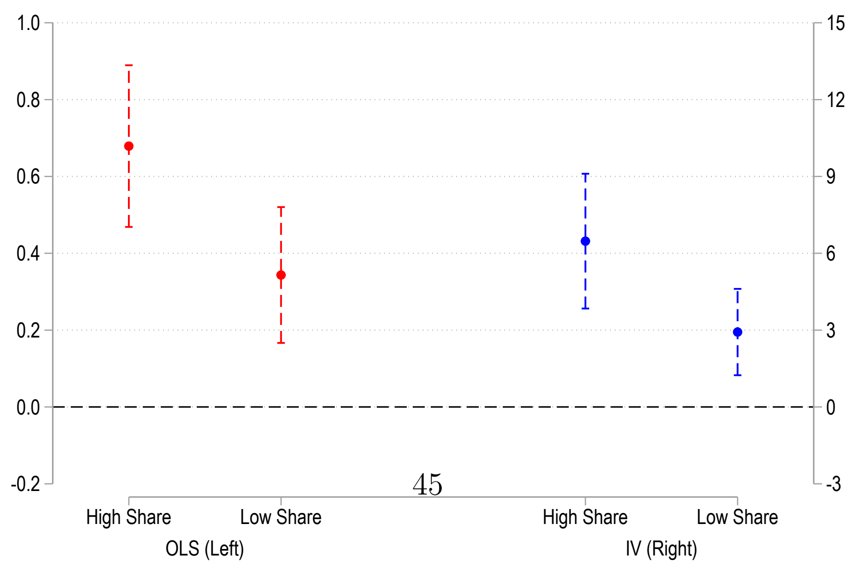


Table 1: Summary Statistics

This table reports summary statistics for main variables. The sample includes 3,083 unique counties from 1990 to 2020. All dollar values are adjusted for inflation to 2020 dollars. All variables are winsorized at the 1st and 99th percentiles. Table A.1 provides detailed variable definitions.

	Obs.	Mean	Min.	25%	Median	75%	Max.	S.D.
Employment (Thousand)	95,209	31.511	0.130	2.103	6.280	19.067	559.783	81.328
Dividends (Million)	95,209	47.271	0.192	2.282	6.566	22.944	1027.200	141.080
Other Income (Billion)	95,209	3.754	0.040	0.363	0.853	2.367	64.833	9.376
Job Creation (Thousand)	95,209	4.438	0.016	0.272	0.810	2.531	82.370	11.924
Job Destruction (Thousand)	95,209	4.091	0.016	0.264	0.767	2.364	75.669	10.963
Net Job Creation (Thousand)	95,209	0.366	-5.456	-0.087	0.032	0.302	12.818	1.964
Dividends/Emp (Thousand)	95,209	1.438	0.250	0.791	1.149	1.675	7.028	1.094
Job Creation/Emp (%)	95,209	13.954	5.027	10.475	13.098	16.315	35.420	5.219
Job Destruction/Emp (%)	95,209	13.060	5.316	10.180	12.362	15.087	30.137	4.342
Net Job Creation/Emp (%)	95,209	0.902	-17.355	-2.137	0.919	3.829	21.389	5.926
Estab Entry/Emp (%)	95,209	0.847	0.000	0.527	0.724	1.029	2.976	0.496
Estab Exit/Emp (%)	95,209	0.811	0.000	0.520	0.696	0.977	2.715	0.452
Net Estab Entry/Emp (%)	95,209	0.037	-1.289	-0.095	0.026	0.164	1.441	0.356
Other Income/Emp (Thousand)	95,209	163.725	67.607	110.761	142.934	191.281	516.522	79.085
Population (Thousand)	95,209	82.763	1.053	10.888	24.819	63.188	1202.256	178.391
Population Growth	95,209	0.005	-0.033	-0.004	0.003	0.012	0.053	0.015
Div Ratio	95,209	0.016	0.003	0.010	0.014	0.019	0.052	0.009
Unemployment Rate	95,209	6.062	2.000	4.100	5.500	7.500	15.200	2.725
% Age Above 65	95,209	16.077	6.426	12.964	15.636	18.791	29.054	4.522

Table 2: The Effect of Dividends on Job Creation

This table presents OLS regression results from Equation 1, examining the effect of county-level dividends on local jobs. The sample includes 3,083 unique counties from 1990 to 2020. *Job Creation/Emp* is the number of jobs created divided by total employment. *Job Destruction/Emp* is the number of jobs eliminated divided by total employment. *Net Job Creation/Emp* is the number of jobs created minus jobs eliminated divided by total employment. *Dividends/Emp* is the dividend income divided by total employment. Jobs variables are measured from March of year $t+1$ to March of year $t+2$, while all other variables are measured in year t. All variables are winsorized at the 1st and 99th percentiles. All specifications include county and state×year fixed effects. t-statistics reported in the parentheses are based on standard errors clustered at the county level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Table A.1 provides detailed variable definitions.

	(1)	(2)	(3)	(4)	(5)	(6)
	Job Creation/Emp		Job Destruction/Emp		Net Job Creation/Emp	
Dividends/Emp	0.182***	0.262***	−0.119***	−0.128***	0.317***	0.406***
	(3.69)	(5.14)	(−2.82)	(−2.89)	(5.62)	(6.85)
Other Income/Emp	0.031***	0.031***	−0.009***	−0.009***	0.039***	0.038***
	(26.50)	(26.27)	(−8.90)	(−8.60)	(29.63)	(29.03)
Div Ratio × Return		0.156		0.023		0.169
		(1.35)		(0.24)		(1.13)
Ln(Population)		−2.905***		0.350		−3.302***
		(−11.15)		(1.64)		(−11.78)
Population Growth		13.351***		3.355*		9.956***
		(6.33)		(1.94)		(3.96)
Unemployment Rate		0.117***		0.038**		0.074***
		(5.56)		(2.33)		(3.25)
% Age Above 65		−0.076***		−0.048***		−0.029
		(−3.29)		(−2.76)		(−1.18)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	95,209	95,209	95,209	95,209	95,209	95,209
Within R^2	0.040	0.045	0.005	0.006	0.038	0.041

Table 3: Instrumental Variable Estimation

This table presents IV regression results examining the effect of county-level dividends on local jobs. The sample includes 3,083 unique counties from 1990 to 2020. Column (1) reports the first-stage estimation results. *Dividends/Emp* is the dividend income divided by total employment. Its instrument, $Dividends^{Proj}/Emp$, is constructed as the product of county-to-nation dividend share in 1989 and aggregate dividends across all other counties in the same year divided by total employment. Columns (2)-(4) report the second-stage estimation results. *Job Creation/Emp* is the number of jobs created divided by total employment. *Job Destruction/Emp* is the number of jobs eliminated divided by total employment. *Net Job Creation/Emp* is the number of jobs created minus jobs eliminated divided by total employment. Jobs variables are measured from March of year $t+1$ to March of year $t+2$, while all other variables are measured in year t. All variables are winsorized at the 1st and 99th percentiles. All specifications include county and state×year fixed effects. t-statistics reported in the parentheses are based on standard errors clustered at the county level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Table A.1 provides detailed variable definitions.

	1st Stage	2nd Stage		
	(1)	(2)	(3)	(4)
	Dividends/Emp	Job Creation/Emp	Job Destruction/Emp	Net Job Creation/Emp
$Dividends^{Proj}$/Emp	0.200***			
	(8.44)			
Dividends/Emp		2.380***	−1.957***	4.058***
		(4.61)	(−4.76)	(6.16)
Other Income/Emp	0.004***	0.019***	0.002	0.018***
	(16.75)	(6.81)	(0.63)	(5.04)
Div Ratio × Return	0.698***	−1.325***	1.270***	−2.358***
	(18.24)	(−3.46)	(4.08)	(−4.66)
Ln(Population)	1.199***	−4.735***	1.943***	−6.467***
	(16.53)	(−8.69)	(4.40)	(−9.12)
Population Growth	0.108	12.777***	4.118**	8.690***
	(0.34)	(5.72)	(2.23)	(3.10)
Unemployment Rate	0.010***	0.086***	0.064***	0.022
	(2.91)	(3.69)	(3.44)	(0.77)
% Age Above 65	0.029***	−0.133***	0.004	−0.131***
	(5.14)	(−4.13)	(0.17)	(−3.20)
F-stat		71.2		
County FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Observations	95,024	95,024	95,024	95,024
Within R^2	0.171			

Table 4: The Effect of Dividends on Consumption

This table presents OLS and IV regression results examining the effect of county-level dividends on local consumption. The data come from the Census Bureau's Economic Census Program in 1997, 2002, 2007, 2012, 2017, and 2022. The explanatory variables are one year prior to each reporting year. The final data covers 3,083 unique counties. *Retail Trade* is the log of sales in the retail trade sector (NAICS 44-45), scaled by total employment. *Accom.& Food* is the log of sales in the accommodation and food services sector (NAICS 72), scaled by total employment. *Other Sectors* is the log of sales in other sectors, scaled by total employment. *All Sectors* is the log of sales in all sectors, scaled by total employment. *Dividends/Emp* is dividend income divided by total employment. The instrument, $Dividends^{Proj}/Emp$, is constructed as the product of a county's 1989 dividend share and aggregate dividends across all other counties in the same year, scaled by total employment. All other variables are measured in year t. Control variables from Table 2 are included. All variables are winsorized at the 1st and 99th percentiles. Specifications include county and state×year fixed effects. t-statistics reported in the parentheses are based on standard errors clustered at the county level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Table A.1 provides detailed variable definitions.

Panel A: OLS Estimation

	(1) Retail Trade	(2) Accom. & Food	(3) Other Sectors	(4) All Sectors
Dividends/Emp	0.031***	0.017***	0.012	0.036***
	(5.87)	(4.23)	(1.48)	(5.61)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Observations	15,094	13,137	14,992	15,238
Within R^2	0.394	0.334	0.140	0.370

Panel B: IV Estimation

	(1) Retail Trade	(2) Accom. & Food	(3) Other Sectors	(4) All Sectors
Dividends/Emp	0.535***	0.262***	0.455***	0.641***
	(5.93)	(4.97)	(4.99)	(5.97)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Observations	15,073	13,114	14,971	15,215

Table 5: Cross-Sectional Analysis by Tradable, Nontradable, and Other Sectors

This table presents OLS and IV estimates from Equation 1, measuring net job creation by establishments across tradable, non-tradable, and other sectors. The sample includes 3,083 unique counties from 1990 to 2020. The dependent variable is net job creation in different sectors, scaled by total employment. *Tradable* sectors include sectors with NAICS codes of 11, 21, and 31-33. *Nontradable* sectors include sectors with NAICS codes of 44-45 and 72. *Others* include all other sectors. *Dividends/Emp* is dividend income divided by total employment. The instrument, $Dividends^{Proj}/Emp$, is constructed as the product of a county's 1989 dividend share and aggregate dividends across all other counties in the same year, scaled by total employment. Control variables from Table 2 are included. Jobs variables are measured from March of year t+1 to March of year t+2, while all other variables are measured in year t. All variables are winsorized at the 1st and 99th percentiles. Specifications include county and state×year fixed effects. t-statistics reported in the parentheses are based on standard errors clustered at the county level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Table A.1 provides detailed variable definitions.

	OLS			IV		
	(1) Tradable	(2) Nontradable	(3) Others	(4) Tradable	(5) Nontradable	(6) Others
Dividends/Emp	0.057***	0.068***	0.157***	0.533***	0.775***	1.568***
	(3.22)	(3.81)	(5.60)	(3.26)	(5.10)	(5.23)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	95,209	95,209	95,209	95,024	95,024	95,024
Within R^2	0.009	0.009	0.016			

Table 6: The Effect of Dividends on Deposits

This table presents OLS and IV regression results examining the effect of county-level corporate dividends on local bank deposits. The sample includes 3,066 unique counties from 199 to 2020. Δ*Deposits/Deposits* is the change in annual deposits divided by lagged dividend. Δ*Deposits/Pop* is the change in annual deposits divided by lagged population. *Dividends/Emp* is dividend income divided by total employment. The instrument, $Dividends^{Proj}/Emp$, is constructed as the product of a county's 1989 dividend share and aggregate dividends across all other counties in the same year, scaled by total employment. *Dividends/Pop* is the dividend income divided by lagged population. The instrument, $Dividends^{Proj}/Pop$, is constructed as the product of a county's 1989 dividend share and aggregate dividends across all other counties in the same year, scaled by lagged population. Jobs variables are measured from March of year t+1 to March of year t+2, while all other variables are measured in year t. Control variables from Table 2 are included. All variables are winsorized at the 1st and 99th percentiles. Specifications include county and state×year fixed effects. t-statistics reported in the parentheses are based on standard errors clustered at the county level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Table A.1 provides detailed variable definitions.

	OLS		IV	
	(1)	(2)	(3)	(4)
	ΔDeposits/Deposits	ΔDeposits/Pop	ΔDeposits/Deposits	ΔDeposits/Pop
Dividends/Deposits	0.205***		1.332***	
	(4.26)		(4.72)	
Other Income/Deposits	0.014***		0.007***	
	(16.06)		(3.69)	
Dividends/Pop		0.123**		0.582*
		(2.21)		(1.76)
Other Income/Pop		0.029***		0.026***
		(10.81)		(7.94)
Div Ratio × Return	−0.005***	0.077**	−0.019***	−0.029
	(−3.35)	(2.00)	(−4.98)	(−0.34)
Ln(Population)	−0.007*	−0.055	−0.016***	−0.156
	(−1.71)	(−0.60)	(−3.27)	(−1.30)
Population Growth	0.334***	5.794***	0.320***	5.690***
	(13.58)	(10.02)	(12.68)	(9.76)
Unemployment Rate	−0.001***	−0.007	−0.001***	−0.008
	(−3.09)	(−1.26)	(−3.37)	(−1.43)
% Age Above 65	−0.001***	−0.035***	−0.001***	−0.037***
	(−4.47)	(−6.26)	(−5.09)	(−6.43)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Observations	79,210	79,210	79,159	79,159
Within R^2	0.028	0.015		

Table 7: The Effect of Dividends on Small Business Lending

This table presents OLS and IV regression results examining the effect of county-level dividends on local small business lending. The sample includes 3,081 unique counties from 1996 to 2020. "*Total SBL*" includes all small business loans. "*Small Firms*" and "*Large Firms*" refer to loans to establishments with revenues below and above $1 million, respectively. "*Small Loans*," "*Median Loans*," and "*Large Loans*" correspond to loans under $100,000, between $100,000 and $250,000, and between $250,000 and $1 million, respectively. In each column, the dependent variable is the total loan amount in the relevant category scaled by total employment. *Dividends/Emp* is dividend income divided by total employment. The instrument, $Dividends^{Proj}/Emp$, is constructed as the product of a county's 1989 dividend share and aggregate dividends across all other counties in the same year, scaled by total employment. Loan amount variables are measured im year t+1, while all other variables are measured in year t. Control variables from Table 2 are included. All variables are winsorized at the 1st and 99th percentiles. Specifications include county and state×year fixed effects. t-statistics reported in the parentheses are based on standard errors clustered at the county level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Table A.1 provides detailed variable definitions.

Panel A: OLS Estimation

	All	Borrower Size		Loan Size		
	(1) Total SBL	(2) Small Firms	(3) Large Firms	(4) Small Loans	(5) Median Loans	(6) Large Loans
Dividends/Emp	0.653***	0.425***	0.227**	0.404***	0.049	0.199
	(2.63)	(2.68)	(2.18)	(3.75)	(1.12)	(1.33)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	79,861	79,861	79,861	79,861	79,861	79,861
Within R^2	0.009	0.007	0.006	0.020	0.007	0.003

Panel B: IV Estimation

	All	Borrower Size		Loan Size		
	(1) Total SBL	(2) Small Firms	(3) Large Firms	(4) Small Loans	(5) Median Loans	(6) Large Loans
Dividends/Emp	3.036***	2.128**	0.908**	1.638***	0.465**	0.933
	(2.70)	(2.51)	(2.27)	(3.32)	(2.07)	(1.55)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	79,684	79,684	79,684	79,684	79,684	79,684

Table 8: Cross-Sectional Analysis by Establishment Size and Age

This table presents OLS and IV estimates from Equation 1, measuring net job creation by establishments of different sizes and ages. The sample includes 3,083 unique counties from 1990 to 2020. Panel A reports results by establishment size. The dependent variable is net job creation by establishments with different employee ranges, scaled by total employment. "[1,19]", "[20,499]", and "≥500" represent establishments with 1–19, 20–499, and 500 or more employees, respectively. Panel B reports results by establishment age. The dependent variable is net job creation by establishments with different age ranges, scaled by total employment. "[0,5]", "[6,10]", and "≥11" indicate establishments that are 0–5, 6–10, and more than 10 years old, respectively. *Dividends/Emp* is dividend income divided by total employment. The instrument, $Dividends^{Proj}/Emp$, is constructed as the product of a county's 1989 dividend share and aggregate dividends across all other counties in the same year, scaled by total employment. Control variables from Table 2 are included. Jobs variables are measured from March of year t+1 to March of year t+2, while all other variables are measured in year t. All variables are winsorized at the 1st and 99th percentiles. Specifications include county and state×year fixed effects. t-statistics reported in the parentheses are based on standard errors clustered at the county level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Table A.1 provides detailed variable definitions.

Panel A: Establishment Size

	OLS			IV		
	(1) [1,19]	(2) [20,499]	(3) $\geq$ 500	(4) [1,19]	(5) [20,499]	(6) $\geq$ 500
Dividends/Emp	0.123***	0.101***	0.089***	0.753***	1.281***	0.863***
	(5.48)	(3.78)	(3.40)	(4.37)	(4.93)	(3.41)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	95,209	95,209	95,209	95,024	95,024	95,024
Within R^2	0.011	0.013	0.014			

Panel B: Establishment Age

	OLS				IV	
	(1) [0,5]	(2) [6,10]	(3) ≥11	(4) [0,5]	(5) [6,10]	(6) ≥11
Dividends/Emp	0.190***	0.054***	0.081***	1.467***	0.532***	1.189***
	(5.34)	(3.88)	(2.70)	(4.67)	(4.46)	(4.14)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	95,209	95,209	95,209	95,024	95,024	95,024
Within R^2	0.024	0.005	0.009			

Table 9: Cross-Sectional Analysis by Bank Dependence

This table presents OLS and IV estimates from Equation 1, measuring net job creation by establishments in sectors with varying bank dependence. The sample includes 3,083 unique counties from 1990 to 2020. The dependent variable is net job creation in sectors with different bank dependence, scaled by total employment. "*Low*" and "*High*" indicates sectors in the bottom and top half of a sector's bank dependence, respectively. A sector's bank dependence is measured as the fraction of firms within that sector that used bank loans to start or expand their businesses, based on the 2007 Survey of Business Owners. Table A.6 reports the fraction of bank loan usages and the classification for each two-digit NAICS sector. *Dividends/Emp* is dividend income divided by total employment. The instrument, $Dividends^{Proj}/Emp$, is constructed as the product of a county's 1989 dividend share and aggregate dividends across all other counties in the same year, scaled by total employment. Control variables from Table 2 are included. Jobs variables are measured from March of year t+1 to March of year t+2, while all other variables are measured in year t. All variables are winsorized at the 1st and 99th percentiles. Specifications include county and state×year fixed effects. t-statistics reported in the parentheses are based on standard errors clustered at the county level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Table A.1 provides detailed variable definitions.

	OLS		IV	
	(1) Low	(2) High	(3) Low	(4) High
Dividends/Emp	0.093***	0.197***	0.790***	2.216***
	(5.07)	(5.07)	(4.75)	(5.64)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Observations	95,209	95,209	95,024	95,024
Within R^2	0.010	0.024		

Table 10: Cross-Sectional Analysis by Small and Regional Bank Dominance

This table presents OLS and IV estimates from Equation 1, measuring net job creation in counties with varying levels of small bank dominance. The sample includes 2,799 unique counties from 1994 to 2020. The dependent variable is the net job creation in counties with different small bank share (Panel A) and regional bank share (Panel B), scaled by total employment. A county's small bank share is the deposit-weighted share of branches operated by small banks (banks with total assets below $500 million). A county's regional bank share is the deposit-weighted share of branches operated by regional banks (banks only operate in a single county). "*High Share*" and "*Low Share*" are classified based on the median of the shares each year. *Dividends/Emp* is dividend income divided by total employment. The instrument, $Dividends^{Proj}/Emp$, is constructed as the product of a county's 1989 dividend share and aggregate dividends across all other counties in the same year, scaled by total employment. Control variables from Table 2 are included. Jobs variables are measured from March of year t+1 to March of year t+2, while all other variables are measured in year t. All variables are winsorized at the 1st and 99th percentiles. Specifications include county and state×year fixed effects. t-statistics reported in the parentheses are based on standard errors clustered at the county level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Table A.1 provides detailed variable definitions.

Panel A: The Share of Small Banks

	OLS		IV	
	(1) High Share	(2) Low Share	(3) High Share	(4) Low Share
Dividends/Emp	0.518***	0.413***	8.503***	1.628***
	(5.49)	(4.68)	(3.44)	(3.60)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Observations	40,960	41,066	40,951	41,010
Within R^2	0.054	0.046		

Panel B: The Share of Regional Banks

	OLS		IV	
	(1) High Share	(2) Low Share	(3) High Share	(4) Low Share
Dividends/Emp	0.679***	0.341***	6.713***	3.199***
	(6.35)	(3.80)	(4.78)	(3.60)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Observations	39,191	42,883	39,191	42,822
Within R^2	0.055	0.050		

Table 11: Robustness Check

This table presents OLS and IV estimates from Equation 1 with additional controls included. The sample includes 3,083 unique counties from 1990 to 2020. The dependent variable is the net job creation, scaled by total employment. *Ln(GDP)* is the log of county-level GDP. *GDP Growth* is the county-level GDP growth rate. *Entrepreneurial Quality* is the county-level Entrepreneurial Quality Index constructed by Fazio et al. (2019) and Guzman and Stern (2020). This index measures the average growth potential of new firms. *Credit Supply* is a measure of credit supply of local small business lending following the approach in Greenstone et al. (2020). *% Bachelor's Degree* is the percentage of population above 25 years with a bachelor's degree. *House Price Growth* is the house price growth rate, measured as the percentage change in the county-level house price index. *Public Firm* (=1) is an indicator variable, equal to one if a county has at least a public firm headquartered locally. *Firm Sale Growth* and *Firm Employ Growth* are the asset-weighted sale growth rate and employment growth rate of local public firms, respectively. Columns (7) and (8) restrict the sample to counties with at least one publicly listed firm headquartered locally. Control variables in Table 2 are included. The instrument, $Dividends^{Proj}/Emp$, is constructed as the product of a county's 1989 dividend share and aggregate dividends across all other counties in the same year, scaled by total employment. Control variables from Table 2 are included. Jobs variables are measured from March of year t+1 to March of year t+2, while all other control variables are measured in year t. All variables are winsorized at the 1st and 99th percentiles. Specifications include county and state×year fixed effects. t-statistics reported in the parentheses are based on standard errors clustered at the county level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Table A.1 provides detailed variable definitions.

Panel A: OLS Estimation

	Net Job Creation/Emp							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dividends/Emp	0.470***	0.441***	0.474***	0.400***	0.417***	0.406***	0.356***	0.374***
	(6.32)	(6.56)	(6.64)	(6.68)	(5.56)	(6.84)	(2.96)	(3.00)
Ln(GDP)	−1.454***							
	(−5.12)							
GDP Growth	1.385***							
	(3.26)							
Entrepreneurial Quality		−46.599						
		(−0.34)						
Credit Supply			0.128					
			(0.89)					
% Bachelor's Degree				0.022				
				(1.06)				
House Price Growth					0.024***			
					(3.96)			
Public Firm (=1)						0.152**		
						(2.35)		
Public Firm Sale Growth							−0.040	
							(−0.51)	
Public Firm Employ Growth								−0.345**
								(−2.48)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58,375	80,508	73,349	95,176	73,871	95,209	16,980	15,607
Within R^2	0.056	0.044	0.049	0.041	0.048	0.041	0.045	0.047

Panel B: IV Estimation

	Net Job Creation/Emp							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dividends/Emp	4.873***	4.133***	3.590***	4.107***	3.857***	4.055***	1.899***	1.893***
	(6.00)	(7.21)	(5.47)	(6.09)	(5.99)	(6.15)	(3.76)	(3.62)
Ln(GDP)	−0.669*							
	(−1.81)							
GDP Growth	1.658***							
	(3.57)							
Entrepreneurial Quality		−126.144						
		(−0.88)						
Credit Supply			0.021					
			(0.14)					
% Bachelor's Degree				−0.120***				
				(−2.99)				
House Price Growth					0.020***			
					(3.30)			
Public Firm (=1)						0.115		
						(1.45)		
Public Firm Sale Growth							−0.022	
							(−0.27)	
Public Firm Employ Growth								−0.313**
								(−2.24)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58,218	80,395	73,217	95,024	73,853	95,024	16,976	15,592

Appendix

Figure A1: Autocorrelation of County-Level dividend share

This figures shows the autocorrelation of county-level dividend share. The dividend share is calculated as a county's dividends divided by aggregate dividends in all counties.

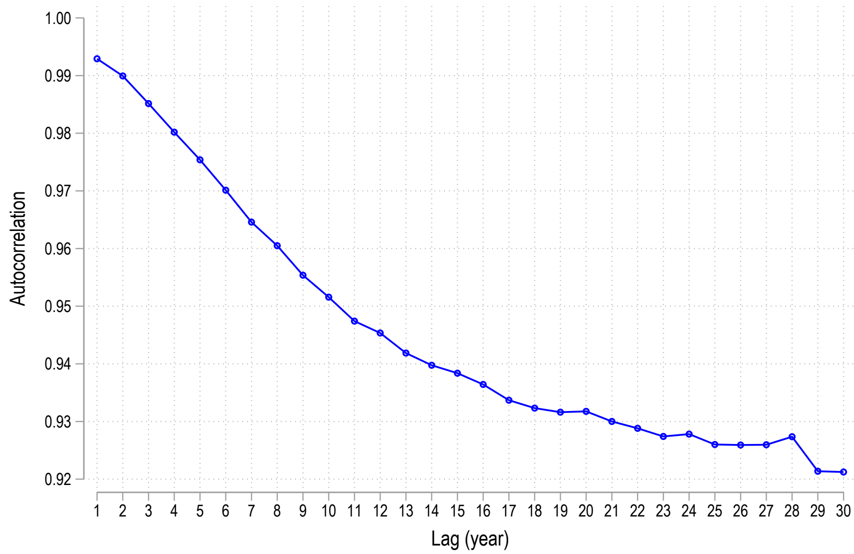


Figure A2: The Dynamic Effect from 1990 to 2020

This figure plots the coefficients β_k from the regression $\frac{Net\ Job\ Creation_{i,t+1}}{Emp_{i,t}} = \beta \frac{Dividends_{i,t}}{Emp_{i,t}} + \gamma' X_{i,t} + \eta_i + \mu_{s,t} + \epsilon_{i,t}$ using rolling three-year windows (four years for the final period) spanning 1990 to 2020. *Net Job Creation/Emp* is the number of jobs created minus jobs eliminated divided by total employment. *Dividends/Emp* is the dividend income divided by total employment. Control variables are same as those in Table 2. All variables are winsorized at the 1st and 99th percentiles. All specifications include county and state×year fixed effects. Standard errors are clustered at the county level. The dash lines plot the 95% confidence intervals of β_k.

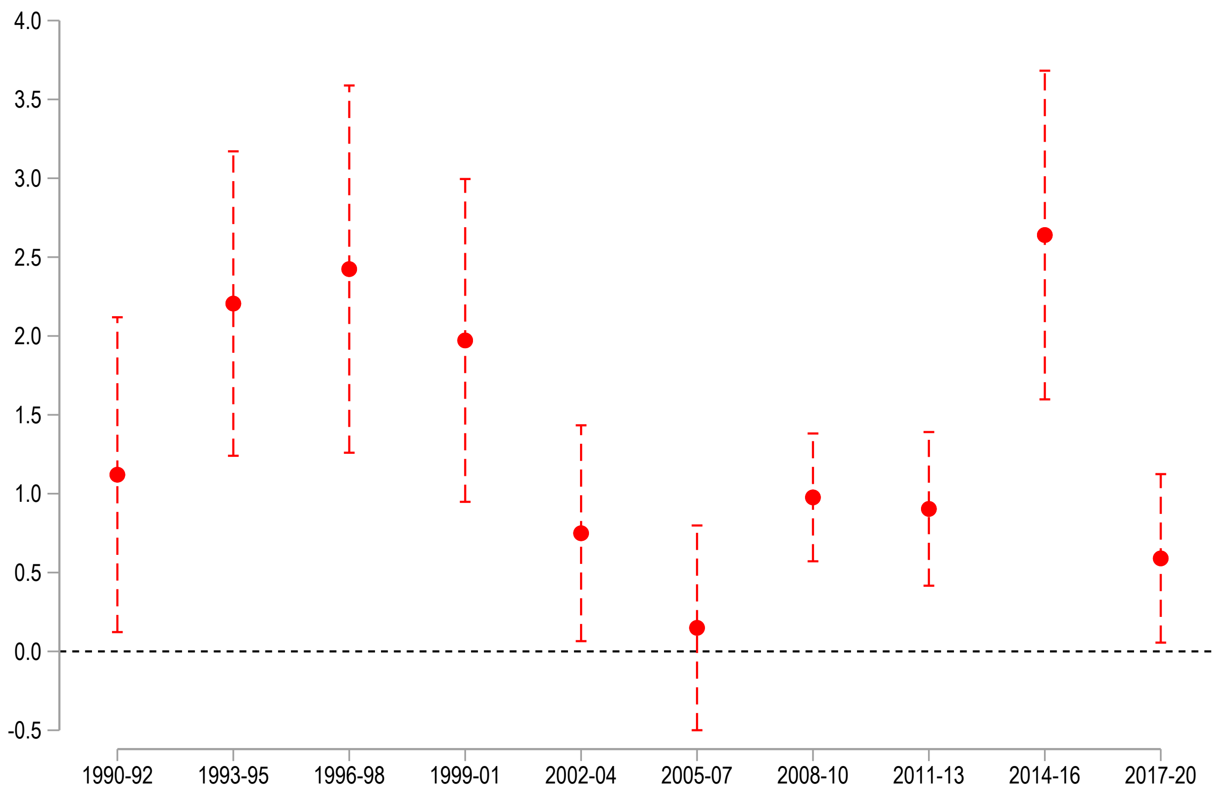


Table A.1: Variable Definitions and Data Sources

Panel A presents county-level variable definitions and data sources. "EC" stands for Census Bureau's Economic Census Program. "BDS" stands for Census Bureau's Business Dynamics Statistics Program. "CBP" stands for Census Bureau's County Business Patterns Program. "BEA" stands for the Bureau of Economic Analysis. "SOD" stands for the FDIC's Summary of Deposits. "CRA" stands for the Community Reinvestment Act. "SBA" stands for the Small Business Administration. "IRS" stands for the Internal Revenue Service. "USDA" stands for U.S. Department of Agriculture. "FHFA" stands for Federal Housing Finance Agency.

Variable	**Definition**	**Sources**
Job Creation/Emp	The number of jobs created divided by total employment.	BDS
Job Destruction/Emp	The number of jobs eliminated divided by total employment.	BDS
Net Job Creation/Emp	The net number of jobs created (jobs created minus jobs eliminated) divided by total employment.	BDS
Dividends/Emp	The dividend income divided by total employment.	IRS & BDS
Dividends/Pop	Dividend income in a county divided by lagged population.	IRS & BEA
Dividends^{Proj}/Emp	Instrumented dividends divided by total employment. Dividends^{Proj} is constructed as the product of a county's 1989 dividend share and aggregate dividends across all other counties in the same year.	IRS & BD
Dividends^{Proj}/Pop	Instrumented dividends divided by lagged population. Dividends^{Proj} is constructed as the product of a county's 1989 dividend share and aggregate dividends across all other counties in the same year.	IRS & BEA
Other Income/Emp	The difference between total income and dividend income in a county divided by total employment.	BEA & BDS
Ln(Population)	The log of population in a county.	BEA
Population Growth	Annual population growth rate.	BEA
Unemployment Rate	Unemployment rate in a county.	BLS
% Age Above 65	Percent of population aged 65 years or older.	CB
% Bachelor's Degree	Percent of adults aged 25+ years old with a bachelor's degree or higher.	USDA
Div Ratio	Ratio of dividends to adjusted gross income.	IRS
Return	Annualized value-weighted excluding-dividends market return.	CRSP

Table A.1 (continued)

Variable	Definition	Sources
Ln(Retail Trade)/Emp	The log of sales in the retail trade sector (NAICS 44-45) divided by total employment.	EC
Ln(Accom. & Food)/Emp	The log of sales in the accommodation and food services sector (NAICS 72) divided by total employment.	EC
Ln(Other Sectors)/Emp	The log of sales in other sectors exlucluding the retail trade and accommodation and food services sector divided by total employment.	EC
Ln(All Sectors)/Emp	The log of sales in all sectors divided by total employment.	EC
ΔDeposits/Deposits	The change in annual deposits in a county divided by lagged deposits.	SOD
ΔDeposits/Pop	The change in annual deposits in a county divided by lagged population.	SOD & BEA
SBL/Emp	The number of small business loans divided by employment.	CRA & BDS
Ln(GDP)	The natural logarithm of county-level GDP in year t.	BEA
GDP Growth	The annual growth rate of county-level GDP.	BEA
Entrepreneurial Quality	The Entrepreneurial Quality Index measuring the average growth potential of new firms.	Fazio et al. (2019)
Credit Supply	A measure of local small business credit supply.	Author calculated
% Bachelor's Degree	The percentage of the population aged 25 and older with a bachelor's degree.	USDA
House Price Growth	The annual growth rate of the county-level house price index.	FHFA
Public Firm (=1)	An indicator equal to one if a county has at least one public firm headquartered locally.	Compustat
Firm Sale Growth	The asset-weighted annual sales growth rate of local public firms.	Compustat
Firm Employ Growth	The asset-weighted annual employment growth rate of local public firms.	Compustat

Table A.2: Household Dividend Consumption and Reinvestment Rates

This table summarizes household consumption and reinvestment rates in response to dividend income in prior studies.

Paper	Country	Sample Period	Consumption Rate	Reinvestment Rate
Baker et al. (2007)	US	1988–2001	16%	–
Kaustia and Rantapuska (2012)	Finland	1995–2002	–	0.7%–1.7%
Di Maggio et al. (2020)	Sweden	1999–2007	39%–60%	18–46%
Bräuer et al. (2022)	Germany	2017–2019	14%	9%
Müller-Dethard et al. (2025)	Germany	2007–2011	12%	80%

Table A.3: Correlation between Dividend Variables

This table presents pairwise correlations between county-level dividends and corporate payouts. *Dividends* represents the county-level dividend. *Dividends*^{Proj} is the shift-share instrument for *Dividends*, calculated as the product of a county's lagged dividend share and the aggregate dividends across all counties in the same year. *Dividends*^{Res} captures the county-specific component of dividends, calculated as the difference between *Dividends* and *Dividends*^{Proj}. *Compustat Dividend* is the total dividends paid by all Compustat firms in a year. *Compustat Repurchase* is the total share repurchases by all Compustat firms in a year. *Compustat Payouts* represents net payouts (dividends and net repurchases) by all Compustat firms in a year. All values are adjusted for inflation to 2020 dollars. *P*-values are shown in parentheses.

	Dividends	Dividends^{Proj}	Dividends^{Res}	Compustat Dividends	Compustat Repurchase	Compustat Payouts
Dividends	1.000					
Dividends^{Proj}	0.937***	1.000				
	(0.00)					
Dividends^{Res}	0.366***	0.019***	1.000			
	(0.00)	(0.00)				
Compustat Dividends	0.059***	0.064***	-0.000	1.000		
	(0.00)	(0.00)	(0.94)			
Compustat Repurchase	0.048***	0.052***	-0.000	0.786***	1.000	
	(0.00)	(0.00)	(0.94)	(0.00)		
Compustat Payouts	0.055***	0.060***	-0.000	0.915***	0.969***	1.000
	(0.00)	(0.00)	(0.94)	(0.00)	(0.00)	

Table A.4: Alternative Instrumental Variable

This table presents IV regression results estimating the effect of county-level dividends on local jobs and establishments using an alternative shift-share instrument. The instrument for $Dividends_{i,t}$ is constructed as the sum of projected dividends across five age brackets: "under 35," "35–44," "45–54," "55–64," "65 and above." The projected number of dividend returns in each age bracket in year t is calculated by multiplying the total number of dividend returns in county i in 2006 ($\#Dividends_{i,b}^{2006}$) by the national share of dividend in age bracket b in 2006 ($Dividend\ share_b^{2006}$), which is the projected number of dividends in this bracket in 2006, and then adjusting for population growth up to year t. This approach assumes that the share of households holding dividend-paying stocks is constant across age brackets and over time. The formal construction is:

$$Dividends_{i,t}^{proj2} = \sum_{b=1}^{5} \underbrace{\overbrace{\#Dividends_{i,b}^{2006} \times Dividend\ share_b^{2006}}^{\text{projected \# dividends in bracket } b \text{ in 2006}} \times (1 + Pop\ growth_{i,t})}_{\text{projected \# dividends in age bracket } b \text{ in year } t} \times \$Dividends\ per\ return_{b,t}.$$

The sample includes 3,077 unique counties from 2007 to 2020. Column (1) reports the first-stage estimation results. *Dividends/Emp* is the dividend income divided by total employment. Its instrument is $Dividends^{Proj2}/Emp$. *Job Creation/Emp* is the number of jobs created divided by total employment. *Job Destruction/Emp* is the number of jobs eliminated divided by total employment. *Net Job Creation/Emp* is the number of jobs created minus jobs eliminated divided by total employment. Jobs variables are measured from March of year t+1 to March of year t+2, while all other variables are measured in year t. All variables are winsorized at the 1st and 99th percentiles. All specifications include county and state×year fixed effects. t-statistics reported in the parentheses are based on standard errors clustered at the county level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Table A.1 provides detailed variable definitions.

	1st Stage	2nd Stage		
	(1)	(2)	(3)	(4)
	Dividends/Emp	Job Creation/Emp	Job Destruction/Emp	Net Job Creation/Emp
Dividends^{Proj2}/Emp	0.101***			
	(6.33)			
Dividends/Emp		13.807***	−11.426***	24.381***
		(5.90)	(−5.76)	(6.30)
F statistic		40.1		
County FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Observations	Yes	Yes	Yes	Yes
Within R^2	42,735	42,735	42,735	42,735
r2_within	0.080			

Table A.5: The Effect of Dividends on Wage and Establishments

This table presents OLS and IV regression results examining the effect of county-level dividends on wage (Panel A) and establishment (Panels B and C). The sample includes 3,078 unique counties from 2001 to 2020. In Panel A, *Wage/Emp* is the total payroll in private sectors, scaled by total employment in year t. The wage data is obtained from Quarterly Census of Employment and Wages (QCEW) program. In Panel B, *Estab Entry/Emp* is the number of new establishments in a county, scaled by total employment. *Estab Exit/Emp* is the number of existing establishments exited the market in a county, scaled by total employment. *Net Estab Entry/Emp* is the difference between *Estab Entry/Emp* and *Estab Exit/Emp*. In Panel C, the dependent variable is *Net Estab Entry/Emp* in different size range. "[1,19]", "[20,499]", and "≥500" represent establishments with 1–19, 20–499, and 500 or more employees, respectively. *Dividends/Emp* is dividend income divided by total employment. The instrument, $Dividends^{Proj}/Emp$, is constructed as the product of a county's 1989 dividend share and aggregate dividends across all other counties in the same year, scaled by total employment. Wage is measured in year t+1. Establishment variables are measured from March of year t+1 to March of year t+2, while all other variables are measured in year t. Control variables from Table 2 are included. All variables are winsorized at the 1st and 99th percentiles. Specifications include county and state×year fixed effects. t-statistics reported in the parentheses are based on standard errors clustered at the county level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Table A.1 provides detailed variable definitions.

Panel A: Wages

	OLS	
	(1)	(2)
	Wage/Emp	Wage/Emp
Dividends/Emp	0.521***	3.743***
	(3.40)	(2.92)
Controls	Yes	Yes
County FE	Yes	Yes
State×Year FE	Yes	Yes
Observations	92,113	91,940
Within R^2	0.106	

Panel B: Establishments

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	Estab Entry/Emp	Estab Exit/Emp	Net Estab Entry/Emp	Estab Entry/Emp	Estab Exit/Emp	Net Estab Entry/Emp
Dividends/Emp	0.033***	0.024***	0.005	0.162***	0.113***	0.021
	(6.06)	(4.57)	(1.29)	(3.47)	(2.65)	(0.75)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	95,209	95,209	95,209	95,024	95,024	95,024
Within R^2	0.053	0.035	0.007			

Panel C: Establishments by Size Range

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	[1,19]	[20,499]	≥500	[1,19]	[20,499]	≥500
Dividends/Emp	0.004	0.001*	−0.000	−0.003	0.004**	0.001
	(1.17)	(1.91)	(−0.44)	(−0.13)	(2.06)	(0.56)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	95,209	95,209	95,209	95,024	95,024	95,024
Within R^2	0.005	0.001	0.003			

Table A.6: Bank Loan dependence by Sectors

This table reports the percentage of establishments that used bank loans to start or expand their businesses across two-digit NAICS sectors, based on the 2007 Survey of Business Owners. An establishment is classified as using bank loans if it reported using bank loans as a source of either startup or expansion capital. *Bank Loan (%)* indicates the percentage of establishments within each sector that reported using bank loans. Sectors are grouped into *Low* and *High* dependence based on the median of *Bank Loan (%)*.

NAICS	Industry Name	Bank Loan (%)	Dependence
61	Educational Services	9.39	Low
71	Arts, Entertainment, and Recreation	12.24	Low
52	Finance and Insurance	14.92	Low
54	Professional, Scientific, and Technical Services	15.25	Low
51	Information	16.53	Low
81	Other Services (except Public Administration)	18.31	Low
56	Administrative and Support and Waste Management and Remediation Services	18.79	Low
22	Utilities	21.25	Low
23	Construction	22.89	Low
53	Real Estate and Rental and Leasing	24.57	High
62	Health Care and Social Assistance	25.73	High
44-45	Retail Trade	27.60	High
11	Agriculture, Forestry, Fishing and Hunting	30.67	High
21	Mining, Quarrying, and Oil and Gas Extraction	31.37	High
48-49	Transportation and Warehousing	32.33	High
42	Wholesale Trade	36.28	High
31-33	Manufacturing	36.41	High
72	Accommodation and Food Services	38.19	High
55	Management of Companies and Enterprises	55.65	High

Table A.7: Cross-Sectional Analysis by Bank Dependence: Alternative Measure

This table presents OLS and IV regression results examining the effect of county-level dividends on job creation by local establishments in sectors with varying bank dependence using an alternative measure for bank dependence.. The sample includes 3,083 unique counties from 1990 to 2020. The dependent variable is the log of job creation in different sectors. "*Low*" and "*High*" indicates sectors in the bottom and top half of a sector's bank dependence, respectively. Following Gilje (2019), a firm's external finance requirement is calculated as $\frac{\sum_{t=1990}^{2020}(Capital\ Expenditures_{n,t} - Operating\ Cash\ Flow_{n,t})}{\sum_{t=1990}^{2020} Capital\ Expenditures_{n,t}}$. A sector's bank dependence is measured as the median external finance requirement of firms within the sector. *Dividends/Emp* is dividend income divided by total employment. The instrument, $Dividends^{Proj}/Emp$, is constructed as the product of a county's 1989 dividend share and aggregate dividends across all other counties in the same year, scaled by total employment. Control variables from Table 2 are included. All variables are winsorized at the 1st and 99th percentiles. Specifications include county and state×year fixed effects. t-statistics reported in the parentheses are based on standard errors clustered at the county level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Table A.1 provides detailed variable definitions.

	OLS		IV	
	(1)	(2)	(3)	(4)
	Low	High	Low	High
Dividends/Emp	0.103***	0.181***	1.110***	1.844***
	(4.18)	(5.45)	(5.21)	(5.03)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Observations	95,209	95,209	95,024	95,024
Within R^2	0.013	0.021		