Geographic Peer Effects in Management Earnings Forecasts*

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ABSTRACT

We find that the likelihood that a firm voluntarily provides an earnings forecast is sensitive to the extent to which other firms in the same geographic area provide earnings forecasts. We use instrumental variable techniques to alleviate the concern that these geographic peer effects are driven by omitted economic factors unique to a local area that lead firms to make similar disclosure decisions. Our findings imply that geographic peer effects in disclosure choices arise in part due to firms trying to avoid negative capital market effects induced by market pressure from local institutional investors. The evidence does not suggest that information sharing among firms plays a key role in generating these geographic peer effects.

Keywords: Disclosure, Earnings forecasts, Peer effects, Geography, Local investors

JEL Classifications: M40, M41

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1. Introduction

A fundamental question in accounting research is: how do firms choose their voluntary disclosure policies? While the majority of work on this topic focuses on the influence of firm-specific factors, a few studies show that the disclosure choices of firms in the same industry are also relevant (e.g., Houston et al., 2010; Tse and Tucker, 2010). However, there is no evidence that firms consider the disclosure choices of firms outside their industry, which is surprising given evidence showing that the actions of nearby businesses can affect a firm (e.g., Jaffe et al., 1993; Kedia and Rajgopal, 2009; Dougal et al., 2015). In this study, we attempt to fill this gap by examining whether a firm's choice to provide an earnings forecast is sensitive to the forecast decisions of firms in the same geographic area (geographic peers, henceforth).

The forecast choices of geographic peers could influence a firm's forecast decision for two reasons. First, a firm could follow the disclosure behavior of geographic peers to avoid negative capital market effects. Investors, including institutional investors, have a strong preference for local stocks (e.g., Coval and Moskowitz, 1999, 2001; Ivković and Weisbenner, 2005). This preference leads to geographically-segmented capital markets in which investors make buying and selling decisions by comparing firms in the same area (Pirinsky and Wang, 2010). Because earnings forecasts can provide information that allows investors to better analyze a firm's return potential and use of capital, firms that provide earnings forecasts can experience capital market benefits resulting from reduced information asymmetries (e.g., Diamond and Verrecchia, 1991; Lambert et al., 2007). Thus, if investors consider and price the availability of earnings forecasts when comparing firms in a geographic area, we posit that a firm will have greater incentive to issue earnings forecasts when a larger fraction of its geographic peers forecast to avoid being penalized in capital markets.

Second, a firm's decision to issue an earnings forecast could be sensitive to the forecast choices of nearby firms because a manager is more likely to observe these choices and interact with these peers. This explanation builds on work showing that geographic proximity facilitates information sharing among individuals and firms, resulting in the spread of similar behaviors (e.g., Hong et al., 2004, 2005; Kedia and Rajgopal, 2009; Dougal et al., 2015). We conjecture that a manager is not only more likely to observe the disclosure choices of geographic peers but also can gain insight into the process and potential payoffs of forecasting through direct communication with managers in the local area.

To test whether the earnings forecast behavior of geographic peers affects a firm's disclosure decisions, we begin by classifying each firm by geographic location and industry to identify geographic and industry peer sets. We use the Metropolitan Statistical Area (MSA) of a firm's headquarters to identify its geographic location and assign the firm to one of nine industry SIC code divisions. For a given firm in our sample, we partition all other firms into one of two groups: i) firms operating in the same MSA but in a different industry (geographic peers), and ii) firms operating in the same industry (industry peers). These partitions allow us to separate geographic peer effects from industry peer effects. We then regress a variable indicating whether a firm provides at least one earnings forecast in a fiscal year on a variable capturing the fraction of firms in the same MSA but in a different industry that provided earnings forecasts in the prior year. In addition to controlling for industry peer effects, we also control for a number of firm-level factors that have been shown to predict forecast behavior as well as local per capita income, growth in per capita income, year fixed effects, MSA fixed effects, and firm fixed effects. Importantly, by including firm and MSA fixed effects, we control for any time-invariant firm- and location-level factors and therefore focus on time-series determinants of forecast decisions. Thus, our results cannot be explained by static geographic attributes, such as distance to major financial centers.

Overall, we find that a firm's earnings forecast decision is sensitive to the disclosure decisions of firms headquartered in the same MSA but in a different industry. A one standard deviation increase in the fraction of geographic peers providing an earnings forecast is associated with a 1.8 to 2.0 percentage point increase in the likelihood that a firm issues a forecast. Given that firms in our sample provide an earnings forecast in 43% of firm-years, these values represent increases relative to the mean of 4.2% to 4.7%.

While we interpret our results as evidence that firms consider the forecast choices of geographic peers when deciding whether to forecast, this sensitivity could instead reflect firms independently responding to time-varying shocks in the region (Manski, 1993). For example, firms in the same MSA could be exposed to the same extreme weather events, local elections, and changes in municipal tax rates. If these regional shocks drive firms in an area to make the same disclosure decisions, we cannot interpret the observed similarity in the disclosure choices of geographic peers as a *true* peer effect. To address this concern, we implement instrumental variable regressions using instruments based on prior work on peer effects (Leary and Roberts, 2014; Dougal et al., 2015; Parsons et al., 2016; Popadak, 2017).

Our first instrument uses the expected likelihood that geographic peers will forecast, where these expectations are derived for each firm using the average fraction of firms in their industry but in different MSAs that provide forecasts. This instrument should meet the relevance condition because there is a strong industry-specific component to forecast decisions (e.g., Brown et al., 2006; Tse and Tucker, 2010; Allee et al., 2015). The exclusion restriction is that the disclosure decisions of firms outside a firm's industry and MSA should only influence the firm's disclosure choice through the disclosure decisions of geographic peers. We believe this is a reasonable assumption given the lack of obvious commonalities between a firm and those firms outside its geographic area and industry.

Our second instrument is the average idiosyncratic stock return volatility of geographic peers. This instrument should meet the relevance condition because firms with higher risk, including higher stock return volatility, are significantly less likely to issue an earnings forecast (e.g., Nagar et al., 2003). Further, because idiosyncratic risk is unpredictable and unique to an individual firm, other firms' idiosyncratic risk should not be directly linked to a manager's own forecast decision. Rather, other firms' idiosyncratic risk works via the impact on peers' forecast decisions, and therefore, this instrument should also meet the exclusion restriction. We use the two instruments separately as well as together, and in all cases, continue to find a positive relation between the fraction of geographic peers that forecast and the likelihood that a firm forecasts.

Next, we try to disentangle the channels that could give rise to geographic peer effects in forecast decisions. As mentioned, geographic peer effects could arise through two non-mutually exclusive channels. The first channel is that firms will follow the disclosure decisions of their geographic peers to avoid capital market penalties. One prediction of this channel is that, if investors value the availability of earnings forecasts when comparing firms in their local area, then a firm's costs of non-disclosure will increase when there is a larger base of local investors and a greater fraction of geographic peers that forecast. Thus, we expect that a firm will be more likely to follow the disclosure policies of geographic peers when it is exposed to a larger base of local investors. We build on prior literature that documents institutional owners' preferences for voluntary disclosures (e.g., Healy et al., 1999; Ajinkya et al., 2005) to test this prediction and capture a firm's exposure to local investors using institutional investors located in its MSA. We find evidence consistent with the prediction that firms are significantly more likely to follow the disclosure decisions of geographic peers when they have a larger base of local institutional investors.

A broader prediction of this channel is that, due to investors valuing earnings forecasts when making investment decisions, a firm will experience relatively lower demand for its stock and lower liquidity if it does not forecast and a greater fraction of its geographic peers forecast. To test this prediction, we capture a firm's stock liquidity using bid-ask spreads, dollar trading volume, share turnover, and the illiquidity measure from Amihud (2002). We find that firms that do not forecast face higher illiquidity when a larger fraction of their geographic peers forecast, but these negative capital market effects are lessened when the firm also forecasts. Together with the prior results, these findings suggest that geographic peer effects in earnings forecasts arise in part due to firms trying to avoid negative capital market effects induced by market pressure from local institutional investors.

The second channel is that a manager will observe and learn from the disclosure choices of firms in the same geographic area. To test for this channel, we follow Karlsson and Manduchi (2001) and Core et al. (2016) and use a measure that captures the density of firms in a geographic area. We expect that both a larger number of firms in an area and shorter distances among these firms will increase the visibility of firm decisions and facilitate interactions among managers. However, our results do not support this channel. Specifically, the positive relation between a firm's disclosure choice and the fraction of geographic peers that forecast does not vary with the density of firms in the area.

A possible alternative explanation for our findings is that, instead of firms responding to the forecasting decisions of their geographic peers, firms and their geographic peers share managers, board members, analysts, or institutional investors who have a preference for a disclosure policy, which leads to common decisions (Jung, 2013; Cai et al., 2014). However, our findings are not consistent with this explanation. After excluding geographic peers that have common managers, board members, analysts, or institutional investors with a firm, we continue to find geographic peer effects in firms' forecast decisions.

Finally, we conduct a number of robustness tests. For example, given the importance of classifying firms as non-industry local peers and industry peers, we show that our results are not sensitive to the choice of industry definition. Specifically, we find similar results when we use the 10-K text-based industry measure developed by Hoberg and Phillips (2010, 2016), two-digit SIC codes, and various Fama-French industry classifications. We also exclude the largest geographic areas from our analysis to ensure that our results are not driven by a few prominent regions. Further, our findings are similar if we: i) use the number of times a firm issues an earnings forecast during a year as our dependent variable (instead of our forecast indicator variable), and ii) control for the firm's forecast decision in the prior year.

Our paper makes three primary contributions. First, we extend research that examines the determinants of voluntary disclosures. Prior work documents that managers weigh a number of expected costs and benefits when choosing to provide an earnings forecast, including costs related to product market effects and legal or regulatory actions as well as benefits from the potential to reduce information asymmetries (e.g., Verrecchia, 1983; Trueman, 1997; Verrecchia, 2001). Information transfers and interactions between firms in an industry also influence disclosure decisions (e.g., Brown et al., 2006; Houston et al., 2010; Tse and Tucker, 2010; Allee et al., 2015; Baginski and Hinson, 2016; Seo, 2016). We build on this literature by showing that the earnings forecast choices of firms in the same geographic area can also affect a firm's propensity to issue an earnings forecast.

Second, we contribute to literature that investigates the significance of peer effects on firm policies, such as capital structure choices, stock splits, and dividend policies (Leary and Roberts, 2014; Kaustia and Rantala, 2015; Popadak, 2017). Prior work also shows that firms in the same geographic area exhibit similar patterns in behavior, arguing that these patterns arise due to local information networks and the spread of social norms (Kedia and Rajgopal, 2009; Dougal et al., 2015; Core et al., 2016; Parsons et al., 2016). While we explore how information sharing among firms in a geographic area might explain similarities in forecast policies, our evidence highlights the influence of geographic peer disclosures via a capital markets channel.

Last, we add to studies documenting the ability of local investors to influence firm policies. Consistent with the notion that proximity to a firm lowers costs of communication and provides more opportunities for interaction with the firm, greater local ownership is associated with increased monitoring and improved corporate governance (e.g., Gaspar and Massa, 2007; Ayers et al., 2011; Chhaochharia et al., 2012). Our study complements this work by highlighting the ability of local investors to influence a firm's forecast choice.

The remainder of the paper proceeds as follows. Section 2 develops our main hypothesis. Section 3 describes our empirical methodology and data. Section 4 presents our main empirical findings. Section 5 discusses additional robustness tests. Section 6 concludes.

2. Hypothesis Development

Accounting information plays a critical role in market-based economies in which firms compete for funds. As outside parties, capital providers value information that allows for improved: i) analysis of the potential return on an investment in a firm, and ii) monitoring of a firm's use of capital (Beyer et al., 2010). Importantly, if information released in voluntary disclosures lowers the risk investors assign to a firm, potential payoffs to the firm include greater interest from investors and financial intermediaries and lower costs of external financing (e.g., Lambert et al., 2007). Thus, factors such as investor demand for information and the opportunity to reduce information asymmetries are central to a manager's choice to disclose more information than required by market regulations (e.g., Diamond, 1985; Diamond and Verrecchia, 1991).

In this paper, we hypothesize that a firm's forecast decision will be sensitive to the forecast choices of geographic peers for two reasons. First, because investors have strong preferences for local stocks, a firm likely has a significant subset of investors who compare the firm to its geographic peers. If a greater fraction of these peers issue forecasts, a firm will have more incentive to issue earnings forecasts to provide investors similar information and mitigate capital market penalties associated with relatively higher information asymmetries.

Second, greater visibility and opportunities for interactions within a geographic area can facilitate information sharing between neighboring firms. A manager could be more likely to observe and/or acquire information about a nearby firm's decisions because of local media coverage or through interactions with common parties. These interactions can facilitate similarities in firm policies, such as rank-and-file employee compensation, investment expenditures, and accrual levels (Kedia and Rajgopal, 2009; Dougal et al., 2015; Core et al., 2016). Because every public firm makes the choice to issue an earnings forecast, a manager's decision to forecast could be disproportionately affected by observing geographic peers' forecast choices to the extent that these choices inform the manager about the forecasting process and potential payoffs. For example, a manager can observe how investors interpret and react to other firms' disclosures or their absence and gain insight into the time and effort required to collect and analyze information through informal communications with other managers.

3. Empirical Methodology and Sample Selection

3.1. General Empirical Methodology

Each observation in our sample represents a firm j in time t that is defined by its headquarters MSA and industry. For a given firm j in time t, we partition all other firms into one of two groups: i) firms operating in the same MSA but in a different industry, and ii) firms operating in the same industry. These partitions allow us to separate geographic peer effects from industry peer effects.

To test whether the earnings forecast behavior of geographic peers affects a firm's propensity to issue an earnings forecast, we estimate the following linear probability model:

$$Forecast_{j,t} = \alpha_1 Forecast_{t-1}^{Non-Ind,Local} + \beta_1 Forecast_{t-1}^{Ind} + X\beta + \upsilon_t + \omega_j + \tau_m + \varepsilon_{j,t}, \qquad (1)$$

where $Forecast_{j,t}$ is an indicator variable that is set to one if firm *j* issues at least one earnings forecast during fiscal year *t* and zero otherwise.[1] $Forecast_{t-1}^{Non-Ind,Local}$ is our variable of interest and equals the fraction of firms (excluding firm *j*) headquartered in the same MSA but in a different industry that provided at least one earnings forecast in the prior fiscal year. We use lagged measures to ensure that peers' forecast decisions are visible to the firm before the firm makes its own disclosure decision. If a firm's disclosure decision is sensitive to the disclosure decisions of its geographic peers, α_1 will be positive. We control for potential industry peer effects by controlling for the fraction of firms (excluding firm *j*) in the same industry that provided at least one earnings forecast in the prior fiscal year $(Forecast_{t-1}^{Ind})$.

X is a set of firm- and MSA-level control variables. The firm-level control variables account for a number of firm-specific factors that have been commonly shown to influence a firm's expected costs and benefits of disclosure and predict forecast behavior, including size, performance, uncertainty, the demand for information, and proprietary costs (e.g., Waymire, 1985; Ajinkya et al., 2005). Therefore, we control for the market value of equity, if a firm reports a loss for the year, earnings and stock return volatility, analyst coverage, institutional ownership, the book-to-market ratio, and industry concentration. The MSA-level control

[1] While the dependent variable *Forecast* is dichotomous, we estimate linear probability models instead of a conditional logistic regressions to avoid the incidental parameters problem and interpretation concerns in regressions with interaction terms. We discuss these concerns in detail and conduct additional robustness tests in Section 5.3.

variables include per capita labor income, the percentage change in per capita labor income, and the number of firms headquartered in an MSA, which account for a number of economic factors that may be spuriously correlated with the likelihood that a firm and its geographic peers provide earnings forecasts. We also include firm fixed effects (ω_j), MSA fixed effects (τ_m), and year fixed effects (ν_t). Importantly, by including firm and MSA fixed effects, we control for any time-invariant firm- and location-level factors (e.g., distance to major financial centers) and therefore focus on time-series determinants of forecast decisions. The year fixed effects account for nation-wide factors, such as country-wide regulations (e.g., Regulation Fair Disclosure) that could affect the likelihood that a firm and its geographic peers provide earnings forecasts. Finally, to correct for heteroskedasticity and correlation of standard errors within firms, we cluster standard errors at the firm level.

Continuous variables, except MSA-level economic variables, are winsorized at their 1st and 99th percentiles, and all dollar values are expressed in 2015 dollars. Table 1 presents detailed definitions and summary statistics for all variables. In our regressions, we standardize all continuous variables to have a mean of zero and a standard deviation of one to ease the interpretation of coefficient estimates. In our sample, firms provide at least one earnings forecast in 43% of firm-years.

3.2. Sample Selection

We begin by using the Institutional Brokers' Estimate System (IBES) to identify all public companies that have at least one analyst providing an annual earnings forecast during a fiscal year for the 1998 to 2015 period.[2] We also obtain from IBES annual and quarterly

[2] Although we use IBES and not First Call's CIG database to acquire management forecast data, we take two measures following guidance in Chuk et al. (2013) to minimize the chance that we misclassify a firm's forecast choice due to incomplete database coverage. Specifically, we: i) collect forecast data beginning in 1998, and ii) require that every firm in our sample have analyst coverage.

management forecasts to identify whether a firm issues an earnings forecast for a given year.[3] Because we require data from the prior year, our panel data set for our regressions covers the years 1999 to 2015.

We classify each firm by geographic location and industry to identify geographic and industry peer sets. We identify a firm's geographic location based on the MSA of its headquarters location.[4] As defined by the Office of Management and Budget (OMB), an MSA is "an area containing a large population nucleus and adjacent communities that have a high degree of integration with that nucleus."[5] Using WRDS SEC Analytics Suite, we acquire the zip code of each firm's historical headquarters location and match this zip code to its corresponding MSA.

To identify a firm's industry, we assign firms to one of nine SIC code divisions: Agriculture, Forestry, and Fishing (0100-0999); Mining (1000-1499); Construction (1500-1799); Manufacturing (2000-3999); Transportation, Communications, Electric, Gas and Sanitary Service (4000-4999); Wholesale Trade (5000-5199); Retail Trade (5200-5999); Finance, Insurance, and Real Estate (6000-6799); and Services (7000-8999). We choose a relatively broader classification to identify a firm's industry to minimize the chance that our geographic peer comparisons are capturing notable industry linkages. However, Section 5.1 shows that our main results hold to using alternative industry classifications.

Last, for our IBES sample with geographic and industry information, we obtain financial statement data from the Compustat annual files, stock return data from the Center for Research in Security Prices (CRSP) files, institutional ownership data from Thomson-

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[3] We exclude forecasts announced after a firm's fiscal year-end, as such forecasts often serve as preliminary earnings announcements (e.g., Rogers and Stocken, 2005).

[4] This choice is consistent with prior literature (see Pirinsky and Wang (2010) for a survey), which recognizes that executives manage a firm from its headquarters location. Further, literature also documents that executives exercise primary responsibility for a firm's voluntary disclosure practices (e.g., Brochet et al., 2011).

[5] See "2010 OMB Standards for Delineating Metropolitan and Micropolitan Statistical Areas", June 28, 2010.

Reuters 13F Data Feed, and MSA-level economic variables from the Bureau of Economic Analysis. This merged sample used to create our measures of geographic and industry peer effects described in the next section has 54,405 firm-year observations. Our final sample used in our regressions consists of 40,771 firm-year observations. This reduction in sample size is due to two reasons. First, to ensure that our peer effect portfolios are reasonably diversified and mitigate the chance that we amplify the influence of a few peers, we require that each sample firm's geographic and industry peer portfolios consist of at least ten firms. This criteria results in deleting 9,047 observations. Second, we require non-missing values for our variables of interest, resulting in further deleting 4,587 observations.

Our final sample contains firms headquartered in 68 different MSAs. Table 2 tabulates the mean number of non-industry local firms in each geographic peer effect portfolio. On average, each portfolio is calculated based on the forecast behavior of 94 firms. Table 2 also shows that the number of non-industry local firms used to calculate the geographic peer effect portfolios varies over time.[6]

4. Empirical Results

4.1. Geographic Peer Effects in Management Earnings Forecasts

We begin our empirical analysis by examining whether a firm's propensity to issue an earnings forecast is associated with the forecast behavior of its geographic peers. Table 3 presents the results of this analysis. The dependent variable in models 1-4 is an indicator variable that is set to one if a firm issues at least one earnings forecast during a fiscal year and zero otherwise.

Model 1 reports the results from a regression model that includes our variable of

[6] We are unable to calculate the standard deviation of the number of non-industry local firms in the geographic peer portfolio for the MSA Lafayette, LA because there is only one firm-year observation for this MSA in our sample. Excluding this MSA from our analysis has no effect on our results.

interest capturing the fraction of local peers outside a firm's industry that forecasted in the prior year, controls for the fraction of industry peers that forecasted in the prior year, and year fixed effects (but not firm and MSA fixed effects). The results show a positive and statistically significant relation between the prior year forecast behavior of geographic peers and the likelihood that a firm issues an earnings forecast in the current year. Specifically, the coefficient estimate of 0.027 implies that, for firms with a one standard deviation higher fraction of geographic peers issuing an earnings forecast during year *t-1*, these firms' propensity to issue an earnings forecast in year *t* is 2.7 percentage points higher. In our sample, firms issue an earnings forecast in 43.0% of firm years. Thus, an increase in the propensity to issue a forecast of 2.7 percentage points represents a relative increase in the likelihood of forecasting of 6.3% (=0.027/0.430). Consistent with prior work (e.g., Brown et al., 2006; Seo, 2016), the results also show that a firm is more likely to issue an earnings forecast when a greater fraction of its industry peers forecasted in the prior year.

Model 2 adds controls for firm characteristics and MSA-level economic variables. Including the full set of control variables slightly lowers the statistical significance and economic effect of geographic peers' forecast behavior on a firm's propensity to issue an earnings forecast. Specifically, in model 2, firms with a one standard deviation higher fraction of geographic peers providing an earnings forecast is associated with a 2.0 percentage point greater likelihood that a firm issues a forecast (an increase of 4.7% relative to the sample mean fraction of forecasting firms).

We note that the coefficient estimates on the control variables are consistent with previous findings. For instance, the likelihood of issuing an earnings forecast is positively related to firm size, the number of analysts following the firm, and institutional ownership. The likelihood of providing an earnings forecast is also negatively related to the occurrence of a loss and the volatility of the firm's earnings and stock returns.

In models 3 and 4, we estimate our preferred regression specifications that focus on time-series variation in the relation between the disclosure decisions of geographic peers and a firm's forecast decision. Specifically, we repeat the analysis in models 1 and 2 but add controls for MSA and firm fixed effects. Consistent with the results from the first two models, we continue to find a positive and statistically significant relation between the forecast decisions of geographic peers and a firm's forecast choice. In terms of economic significance, the results in model 3 (4) imply that a one standard deviation increase in the fraction of geographic peers providing an earnings forecast is associated with a 2.0 (1.8) percentage point increase in the likelihood that a firm issues a forecast (an increase of 4.7% (4.2%) relative to the sample mean fraction of forecasting firms). In sum, the results in Table 3 are consistent with the hypothesis that a firm's choice to issue an earnings forecast is sensitive to the forecasting behavior of its geographic peers.

4.2. Shared Exposure to Common Shocks

We recognize that firms in a geographic area share the same local environment, which can facilitate exposure to common shocks that could independently drive firms to make the same forecast choices. Thus, in this section, we address the explanation that the observed geographic peer effects in earnings forecast policies could be due to firms in the same geographic area responding to common local shocks rather than peer effects. By defining geographic peers as those located in the same MSA but in a different industry, our research design rules out the possibility that firms in the same area are responding to local industry shocks. Instead, firms could be responding to shocks in local economic conditions. We use an instrumental variable strategy to help address this concern and present the results of this analysis in Table 4.

A valid instrumental variable must satisfy two conditions (e.g., Larcker and Rusticus, 2010; Roberts and Whited, 2013). First, the relevance condition requires that the instrument is correlated with the fraction of geographic peers providing an earnings forecast after controlling for the set of control variables in our main model specification. Second, the exclusion restriction requires that, conditioning on the full set of control variables, the instrument is correlated with a firm's propensity to issue an earnings forecast only through its correlation with our measure of geographic peer forecast behavior. Based on these criteria, we identify two plausibly valid instruments.

For our first instrument, we define the variable $\textit{Expected Forecast}_{t-1}^{Non-Ind,Local}$ equal to the expected fraction of firms operating in the same MSA but in a different industry that provide at least one earnings forecast during the fiscal year. To estimate this expectation, we first set the likelihood that each firm will provide an earnings forecast (*Expected Forecast*) to the fraction of firms in the same industry but a different MSA that provide at least one earnings forecast. We then average *Expected Forecast* across all firms in the same MSA but different industry as the firm of interest. This instrument should meet the relevance condition based on our results in Table 3 as well as prior findings which show that the disclosure decisions of industry peers affect a firm's disclosure choice (e.g., Brown et al., 2006; Tse and Tucker, 2010). The exclusion restriction for this instrument is that the disclosure decisions of firms outside a firm's industry and MSA should only influence the firm's disclosure choice through the disclosure decisions of its geographic peers. We believe this is a reasonable assumption given the lack of observable commonalities between a firm and those firms outside its geographic area and industry.

For our second instrument, we follow an approach similar to Leary and Roberts (2014) and Popadak (2017) and use the idiosyncratic stock return volatility of local non-industry peer firms as an instrument for geographic peer influence. To estimate idiosyncratic volatility, we first estimate excess stock returns with the following augmented market model:

$$r_{j,m,t} = \alpha_{j,m,t} + \beta_{j,m,t}^{MKT}(rm_t - rf_t) + \beta_{j,m,t}^{MSA}(\bar{r}_{-j,m,t} - rf_t) + \eta_{j,m,t} \ , \tag{2}$$

where $r_{j,m,t}$ refers to the total return for firm j in MSA m over month t, $(rm_t - rf_t)$ is the excess market return, and $(\bar{r}_{-j,m,t} - rf_t)$ is the excess return on an equal-weighted MSA portfolio excluding firm j's return. This last factor is intended to remove any variation in returns that is common across firms in the same MSA and hence remove local economic shocks. We estimate Eq. (2) for each firm on a rolling annual basis using historical monthly return data over the prior three years (we require firms to have at least 24 months of returns).

Finally, we define each firm's idiosyncratic volatility as the standard deviation of the residuals from the previous regression and use the average idiosyncratic volatility of geographic peers as the instrument ($Avg.Idio.Risk_{t-1}^{Non-Ind,Local}$). This instrument should meet the relevance condition because firms with higher risk, including higher stock return volatility, are significantly less likely to issue an earnings forecast (e.g., Nagar et al., 2003). Further, because idiosyncratic risk is unpredictable and unique to an individual firm, another firm's idiosyncratic risk should not be directly linked to a manager's forecast decision. Rather, other peers' idiosyncratic risk works via the impact on their forecast decisions, and therefore, this instrument should also meet the exclusion restriction.

Table 4 provides the results of two-stage least squares instrumental variable regressions that use $Expected\,Forecast_{t-1}^{Non-Ind,Local}$ and $Avg.Idio.Risk_{t-1}^{Non-Ind,Local}$ as instruments for the fraction of geographic peers issuing forecasts. The first stage results in models 1 and 3 show that $Expected\,Forecast_{t-1}^{Non-Ind,Local}$ and $Avg.Idio.Risk_{t-1}^{Non-Ind,Local}$ are significantly related to the forecast choices of geographic peers. The high F-statistics of the instruments' significance of 921 and 829 imply that the instrumental variables do not suffer from the weak instrument problem. Focusing on the second stage results in models 2 and 4, we continue to find that a firm's forecast choice is significantly and positively related to the forecast behavior of firms in the same MSA but in a different industry. While we use these instruments separately in models 1-4, in models 5 and 6, we include both instruments as predictors of the forecast behavior of geographic peers. Similar to the previous models, we continue to find geographic peer effects in a firm's disclosure decision. In addition, the instruments are highly significant with a joint F-statistic of 844. Further, based on the Hansen J-statistic for overidentification of 0.049 (p-value of 0.82), we are unable to reject the null hypothesis that our instruments are uncorrelated with the error term, lending further support to the notion that our instruments meet the exclusion restriction.

Overall, the results in Table 4 suggest that the observed geographic peer effects in a firm's earnings forecast decision are robust to accounting for the possible explanation that these effects arise from firms in the same MSA responding to shared local shocks.

4.3. Why do Geographic Peer Effects in Earnings Forecasts Arise?

We next conduct empirical tests to understand why a firm's choice to issue an earnings forecast is sensitive to the forecast behavior of its geographic peers. Specifically, we examine whether geographic peer effects in earnings disclosures arise from: i) capital market incentives, and/or ii) information sharing among firms. Importantly, these two channels are not mutually exclusive, and we may find support for both.

4.3.1. Capital Market Incentives

We first test whether geographic peer effects in disclosure choices arise from capital market incentives. To the extent that investors recognize and price the availability of earnings forecasts when comparing firms in a geographic area, we expect that a firm will face higher costs of non-disclosure when it has a larger base of local investors and a greater fraction of its geographic peers issue forecasts. Thus, we predict that the positive relation between a firm's disclosure decision and the disclosure behavior of its geographic peers will be stronger when there are more potential investors in the firm's MSA and when a larger share of the firm is owned by investors in its MSA. We examine this prediction in the following analysis and report the results in Table 5.

We proxy for the presence of local investors by identifying institutional investors located in a firm's MSA.[7] We focus on institutional investors because prior work shows that firms respond to demands from these investors to provide voluntary disclosures (e.g., Healy et al., 1999; Ajinkya et al., 2005). We use five measures to proxy for the presence of local institutional investors: i) *# of IO* is the number of institutional investors located in the same MSA as a firm, ii) *$ of IO* is the total dollar holdings of all institutional investors located in the same MSA as a firm, iii) *# of Existing IO* is the number of institutional investors located in the same MSA as a firm that are invested in the firm, iv) *$ of Existing IO* is the total dollar holdings of all institutional investors located in the same MSA as a firm that are invested in the firm, and v) *Existing % IO* is the fraction of a firm's shares that are owned by institutional investors located in the same MSA as the firm. We interact the natural logarithm of the first four institutional investor variables and *Existing % IO* with $Forecast_{t-1}^{Non-Ind,Local}$ to test our prediction. However, we standardize each institutional investor measure to have a mean of zero and a standard deviation of one before interacting them to ease the interpretation of coefficient estimates.

[7] We thank Gennaro Bernile for sharing this data up to 2010 (e.g., Bernile et al., 2015). We extend the sample to 2015 by obtaining each institutional investors' zip code from SEC filings and Bloomberg.com when SEC filings are unavailable. We then match each zip code to its corresponding MSA.

The results in Table 5 show that the sensitivity of a firm's disclosure decision to the forecast choices of its geographic peers is stronger when: i) there are more institutional investors located in its MSA (model 1), and ii) it is owned by more local institutional investors (models 3-5). We do not find that a firm is more likely to issue an earnings forecast when a greater fraction of its geographic peers forecast and there is a greater amount of institutional holding dollars in the MSA (model 2). In terms of economic significance, the coefficient estimate on $Forecast_{t-1}^{Non-Ind,Local}$ in model 1 implies that, for firms with a mean number of local institutional investors in their MSAs, a one standard deviation increase in the fraction of geographic peers issuing an earnings forecast increases a firm's propensity to issue an earnings forecast by 2.1 percentage points. However, for firms facing a one standard deviation higher number of local institutional investors, a one standard deviation increase in the fraction of geographic peers forecasting is associated with an increase in the likelihood the firm forecasts of 2.9 (=0.021+0.008) percentage points. The economic magnitudes in models 3-5 are similar.

Next, we test the prediction that, if a greater fraction of geographic peers issue forecasts and a firm does not, the firm should experience higher information asymmetry and lower investor demand relative to other firms in the MSA who forecast, leading to lower liquidity (Diamond and Verrecchia, 1991). We test this prediction using four measures that capture the illiquidity of a firm's stock: i) *Illiquidity* follows from Amihud (2002) and is the absolute value of the daily returns divided by the day's dollar trading volume averaged over the firm's fiscal year (multiplied by 10^9), ii) *Bid-Ask Spread* is the daily closing bid-ask spread scaled by the midpoint of the closing bid-ask spread averaged over the firm's fiscal year, iii) *$ Trading Vol* is the daily dollar trading volume averaged over the firm's fiscal year, and iv) *Share Turnover* is the daily number of shares traded scaled by the number of shares outstanding averaged over the firm's fiscal year. Higher values of *Illiquid* and *Bid-Ask Spread* indicate that a stock is more illiquid, while higher values of *$ Trading Vol* and *Share Turnover* indicate the stock is less illiquid. To ease the interpretation of coefficient estimates, we multiply *$ Trading Vol* and *Share Turnover* by minus one so that higher values can be interpreted as greater illiquidity.

We include in our models our indicator variable for whether a firm issues an earnings forecast in year *t* and interact this indicator variable with our primary variable of interest: the fraction of geographic peers that provided at least one earnings forecast in year *t-1*. Thus, the coefficient estimate on $Forecast_{t-1}^{Non-Ind,Local}$ indicates the effect of geographic peer disclosure choices on the stock liquidity of a firm that does not issue a forecast. Importantly, the coefficient estimate of interest on the interaction term $Forecast_{t-1}^{Non-Ind,Local} \times Forecast_t$ indicates whether a firm can mitigate negative capital market consequences by forecasting when a larger fraction of its geographic peers forecast.

Models 1-4 of Table 6 show that firms that do not forecast have higher illiquidity when a larger fraction of their geographic peers forecast. For example, when a firm does not forecast, a one standard deviation increase in the fraction of geographic peers forecasting is associated with 5.6% higher *Illiquidity,* an 8.1% higher *Bid-Ask Spread,* a 5.0% lower *$ Trading Vol*, and 2.9% lower *Share Turnover.* When the firm also forecasts, however, these negative consequences are mitigated but not eliminated (joint F-statistics of 7.09, 36.43, 6.88 and 3.78, respectively).

Overall, the results in Tables 5 and 6 suggest that geographic peer effects in earnings forecast decisions are due in part to firms trying to avoid negative capital market effects that arise from market pressure from local institutional investors.

4.3.2. Information Sharing

Next, we test whether geographic peer effects in disclosure choices arise from information sharing among neighboring firms. Proximity to other firms can increase the visibility of firm decisions and facilitate interactions among managers. To the extent that direct or indirect interactions with other firms inform a manager's decision to forecast, information sharing could explain why a firm's forecast decision is sensitive to the forecast behavior of its geographic peers.

We expect that a larger number of geographic peers will facilitate greater opportunities for interactions among firms and shorter distances between these peers will increase the likelihood that interactions occur. Thus, to examine whether information sharing among firms explains our main results, we create three measures that capture these opportunities for interactions. First, we follow Karlsson and Manduchi (2001) and Core et al. (2016) and use a measure of local firm density (*Density*) that accounts for both the number of geographic peers and the distance between these peers. We calculate *Density* for firm *j* in year *t* using the set of peers that are in the same MSA but in a different industry as follows:

$$Density_{j,t} = \sum_{n=1}^{N_{m,t}-1} e^{-MV_{n,t} \times Distance_{j,n,t}} \quad , \tag{3}$$

where $N_{m,t}$ is the number of local non-industry firms in MSA *m* and year *t*, $Distance_{j,n,t}$ is the distance between firms *j* and *n* in year *t*, and $MV_{n,t}$ is the market value of firm *n* in year *t*. We use the GEODIST function in SAS to calculate the distance between the zip codes of two firms. In the case when two firms have the same zip code, we set the distance equal to half the minimum distance in the MSA-year. This way, we assume that the two firms are located at approximately the radius of the smallest zip code area in the MSA. Higher values of *Density* indicate a larger number of geographic peers (holding distances among these peers constant) or shorter distances among these peers (holding the number of geographic peers constant).

Our second measure captures only the distance between a firm and its non-industry local peers. This measure (*VW Distance*) is the value-weighted distance between a firm and all peers operating in the same MSA but in a different industry, in which weights are based on market capitalization. The third measure (*# Non-Ind Local Firms*) captures the number of firms operating in the same MSA but in a different industry.

To test whether interactions among firms are a channel through which the observed geographic peer effects in forecasting behavior arise, we interact the standardized natural logarithm *t-1* values of these three measures with our primary variable of interest $Forecast_{t-1}^{Non-Ind,Local}$. Table 7 reports the results of this analysis. The results show that, for all three measures, the interaction terms are statistically indistinguishable from zero. Thus, increases in the number of geographic peers and decreases in distances between these peers do not affect the sensitivity of a firm's disclosure choice to the forecast behavior of its geographic peers. Therefore, these results do not support information sharing among firms in a geographic area as a channel generating the observed peer effects.

4.4. Alternative Explanations

A possible alternative explanation for our findings is that, instead of firms responding to the forecasting decisions of their peers, firms and their geographic peers share managers, board members, analysts, or institutional investors who influence firm policies according to their preferences (Jung, 2013; Cai et al., 2014). We test the extent to which this explanation could drive our findings by excluding peers that share these parties with the firm when calculating the geographic peer effect portfolios and report the results in Table 8.

To identify managers and board members that are shared across firms, we obtain data from Boardex. Hence, for our analyses in models 1 and 2, we include only firms and geographic peers that we can match to Boardex. In model 1, we exclude geographic peers that have a board member who is also CEO of the firm. In model 2, we exclude all geographic peers that have a board member who also holds a management or board position at the firm. Next, in model 3, we exclude geographic peers that are covered by an analyst who also covers the firm. Last, in models 4 and 5, we exclude all peer firms that share an important institutional investor with the firm. In model 4, we define important institutional investors as those that own at least 5% of the firms' outstanding shares. In model 5, we broaden the definition of important institutional investors to those that own at least 3% of the firms' outstanding shares.

Overall, across all of the exclusion restrictions, the results continue to show that a firm's forecasting decision is sensitive to the forecasting choices of its geographic peers. Thus, these results suggest that our findings are not completely driven by the firm and its geographic peers having common managers, board members, analysts, or institutional investors.

5. Additional Robustness Tests

5.1. Alternative Industry Definitions

In all of our tests so far, we group firms into one of nine industries based on SIC code divisions. Table 9 shows that the positive relation between the likelihood that a firm provides an earnings forecast and the fraction of its non-industry geographic peers that provide earnings forecasts is robust to grouping firms using alternative industry classifications. Model 1 shows that our results are robust to classifying firms into industries using the 10-K text-based industry measure developed by Hoberg and Phillips (2010, 2016). This measure uses similarities in firm-provided product descriptions to identify a distinct set of competitors for each firm and groups firms into 1 of 25 industries. Importantly, unlike traditional industry classifications (e.g., by SIC or NAICS), this text-based measure incorporates information regarding the degree to which specific firms are similar to their competitors and how this changes over time, resulting in a higher likelihood of identifying peers that a firm reports as rivals (Hoberg and Phillips, 2016). Models 2-5 show that our results are also robust to defining industries by two-digit SIC codes (model 2) as well as Fama-French 12, 17, and 49 industry classifications (models 3-5).

5.2. Using Quarterly Forecasts at the Firm-Year-Quarter Level

Thus far, the unit of observation in our regressions is at the firm-year level and the dependent variable *Forecast* is set to one if the firm provides at least one quarterly or annual earnings forecast during the year. In model 1 of Table 10, we focus our analysis on quarterly earnings forecasts and use quarterly data so that the unit of observation is a firm-year-quarter. We set the indicator variable *Forecast* to one if the firm issues at least one quarterly earnings forecast during the quarter. Consistent with our prior findings, the results show that a firm's propensity to issue a quarterly earnings forecast is positively and statistically significantly related to the fraction of geographic peers providing an earnings forecast in the prior quarter.

5.3. Alternative Model Specifications

A firm's choice to provide an earnings forecast tends to be a relatively persistent policy (e.g., Gibbins et al., 1990). While we include firm fixed effects in our primary tests and thus, focus on changes in a firm's forecast policy, another common approach to account for persistency in disclosure policies is to control for a firm's past disclosure choice (e.g., Brochet et al., 2011). In model 2 of Table 10, we control for whether a firm provided an earnings forecast in the prior year and continue to find that the firm's forecasting decision is sensitive to the forecasting decisions of its geographic peers.

Next, we recognize that an earnings forecast can be qualitative or quantitative and take the form of a point, range, or open-ended forecast. We follow prior literature that highlights the higher precision and prevalence of point and range forecasts (e.g., Baginski and Hassell, 1997; Brochet et al., 2011; Kwak et al., 2012) and identify only those firms that issue a point or range forecast as disclosing firms.[8] On average, 40% of firm-years in our sample provide at least one point or range forecast during the year. Model 3 of Table 10 shows that, when exclusively considering point and range forecasts, we continue to find a positive and statistically significant relation between the forecast choices of geographic peers and the likelihood that a firm forecasts.

While the dependent variable *Forecast* is dichotomous, we estimate the likelihood that a firm provides an earnings forecast using a linear probability model. There are two criticisms generally associated with using linear probability models. First, the standard errors are unavoidably heteroskedastic. We correct for this concern by clustering standard errors by firm, which accounts for heteroskedasticity. Second, predicted values can lie outside the unit interval [0, 1], which could lead to biased and inconsistent estimates. Horrace and Oaxaca (2006) show that, if a very small number of predicted values fall outside the unit interval, then bias and inconsistency is a minor or nonexistent issue. In our main regression from model 4 of Table 3, 4.3% (1,754 out of 40,771 observations) of the predicted values of *Forecast* are outside the unit interval, which is small and therefore any bias should be minimal. Nevertheless, Horrace and Oaxaca (2006) suggest excluding any observations with predicted values outside the unit interval and re-estimating the models to reduce any potential bias.

[8] We follow the classification process in Anilowski et al. (2007) to identify forecasts as point and range forecasts.

We apply this approach and report the results in model 4 of Table 10. The results are nearly identical to those reported in Table 3.

An alternative approach is to estimate a conditional logistic regression, which would allow us to account for firm fixed effects and include year dummy variables. Model 5 of Table 10 shows that our main specification from model 3 of Table 3 is robust to estimating a conditional logistic regression. We note that the sample size decreases from 40,771 to 24,702 observations because the conditional logistic model drops firms that either provide a forecast every year over the sample period or never provide a forecast over the sample period. We do not use the conditional logistic regression for our main analyses for two reasons. First, we are unable to include both year and MSA dummy variables, which is our preferred specification, in the conditional logistic regression because the models do not converge (incidental parameters problem). Second, a number of our tests involve interaction terms. Ai and Norton (2003) demonstrate that neither the direction nor the statistical significance of the coefficient estimates on the interaction terms in nonlinear models (e.g., conditional logistic regressions) are informative. While the authors provide statistical corrections for some models, such as logistic and probit regressions, no corrections are available for conditional logistic regressions.

5.4. Management Earnings Forecast Frequency

Our main dependent variable *Forecast* is a dummy variable indicating whether a firm provides at least one earnings forecast during the fiscal year. During the year, however, managers can frequently update their estimates of future earnings for quarter or annual year-ends. In our sample, 43% of firms provide at least one earnings forecast during the year. Of these firms, 87% provide more than one forecast and 47% provide at least five forecasts during the year. In model 6 of Table 10, we examine the relation between the frequency that a firm provides an earnings forecast and the average forecast frequency of its geographic peers. Specifically, we regress the natural logarithm of one plus the number of forecasts a firm provides throughout its fiscal year on the average of the natural logarithm of one plus the number of forecasts firms in the same MSA but different industry provide during the prior fiscal year. The results are similar to our previous findings. A one standard deviation increase in the number of earnings forecasts firms in the same geographic area provide is associated with a 3.2% increase in the number of earnings forecasts the firm provides.

5.5. Effect of Excluding Prominent Geographic Areas

To ensure that the actions of firms in a single geographic location do not drive our results and therefore speak to the generalizability of our findings, we exclude the most prominent geographic areas from our sample. In our sample, California, Texas, and New York are the three states with the largest concentration of firm headquarters, comprising 21.4%, 10.0%, and 8.8% of our firm-year observations. Thus, in models 1-3 of Table 11, we exclude firms headquartered in these three states in separate regressions, and in model 4, we exclude firms headquartered in any of these three states. In models 5 and 6, we exclude the largest five and ten MSAs from the regressions, respectively. Overall, the results show that the positive relation between a firm's forecasting decisions and the forecasting decisions of its geographic peers is robust to excluding the most concentrated geographic areas from our analysis.

6. Conclusion

In this paper, we show that a firm's decision to provide an earnings forecast is sensitive to the disclosure decisions of firms in the same geographic area but in a different industry. Further, firms' disclosure decisions are more sensitive to the disclosure choices of geographic peers when there is a larger base of local institutional investors, and firms that do not forecast when a larger fraction of their geographic peers forecast face negative capital market effects in the form of lower stock liquidity. Together, these findings imply that geographic peer effects in disclosure choices arise in part due to firms trying to avoid negative capital market effects induced by market pressure from local institutional investors. In addition, we use instrumental variable techniques to help rule out the explanation that these geographic peer effects are driven by omitted economic factors unique to a local area that lead firms to make similar disclosure decisions.

We also test two alternative explanations for our findings. First, we examine whether these geographic peer effects arise due to firms in the same geographic area sharing information. Second, we test whether common decisions arising from firms and their geographic peers sharing managers, board members, analysts, or institutional investors who have a preference for a particular disclosure policy drive our results. Overall, our findings do not suggest that these alternative channels play key roles in generating these geographic peer effects.

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Table 1
Summary Statistics

This table reports summary statistics for the main variables in the regression models. The sample consists of firms that have analyst coverage in the IBES database over the 1999 to 2015 period and includes 40,771 firm-year observations. Continuous variables, except MSA-level economic variables, are winsorized at their 1st and 99th percentiles, and all dollar values are expressed in 2015 dollars. Variable definitions refer to Compustat designations where appropriate. *Forecast* is an indicator variable that is set to one if a firm issues at least one earnings forecast during a fiscal year and zero otherwise. $Forecast^{Non\text{-}Ind,\ Local}$ is the fraction of firms operating in the same MSA but in a different industry that provide at least one earnings forecast during the fiscal year. $Forecast^{Ind}$ is the fraction of firms operating in the same industry that provide at least one earnings forecast during the fiscal year (the firm itself is excluded from the calculation of this variable). Firms are grouped into nine separate industries based on SIC code divisions. *Market Capitalization* is a firm's market value of equity (in $ millions) at the end of a fiscal year (*prcc_f*csho*). *Loss Indicator* is an indicator variable set to one if income before extraordinary items (*ib*) is less than zero and zero otherwise. *Earnings Volatility* is the standard deviation of quarterly ROA (*ibq/atq*) over the previous 12 months (we require firms have at least eight quarterly observations to enter the sample). *Return Volatility* is the annualized standard deviation of daily returns over a firm's fiscal year (we require firms have at least 120 daily return observations during their fiscal year to enter the sample). *Number Analysts* is the average number of analysts following a firm over a fiscal year. *Institutional Ownership* is the fraction of shares owned by institutional owners. *Book-to-Market* is book value of equity divided by market value of equity (*ceq/(prcc_f*csho)*). *Industry HHI* is the sales-based Herfindahl-Hirschman Index of the industry calculated by summing the squares of the ratios of firm sales to the industry's total sales. *P.C. Labor Income* is the MSA-level per capita amount of labor income. *% Change in P.C. Labor Income* is the percentage change in the MSA-level per capita amount of labor income. *# Firms in MSA* is the number of firms headquartered in a firm's MSA.

	Mean	Std. Dev.	P25	Median	P75
Forecast	0.430	0.495	0.000	0.000	1.000
$\text{Forecast}^{\text{Non-Ind, Local}}$	0.396	0.133	0.294	0.400	0.490
$\text{Forecast}^{\text{Ind}}$	0.392	0.145	0.311	0.394	0.498
Market Capitalization	4,824	14,015	217.6	722.3	2,658
Loss Indicator	0.323	0.468	0.000	0.000	1.000
Earnings Volatility	0.033	0.055	0.006	0.013	0.036
Return Volatility	0.546	0.312	0.322	0.464	0.685
Number Analysts	7.415	6.547	2.500	5.250	10.333
Institutional Ownership	0.574	0.275	0.356	0.614	0.802
Book-to-Market	0.544	0.463	0.245	0.445	0.722
Industry HHI	0.022	0.013	0.014	0.016	0.025
P.C. Labor Income	41,962	8,921	35,838	39,451	45,208
% Change in P.C. Labor Income	0.010	0.036	-0.009	0.012	0.031
# Firms in MSA	250.8	230.2	91.00	203.0	282.0

Table 2
Non-Industry Local MSA Portfolio Statistics

This table lists the 68 MSAs in our sample by the average number of non-industry local firms in each portfolio (i.e., $Forecast^{Non\text{-}Ind,\ Local}$) over the years 1999 to 2015 for each MSA.

	Number of Firms				
Metropolitan Statistical Area	Mean	Std. Dev.	P25	Median	P75
New York-Newark-Jersey City, NY-NJ-PA	262	58	216	251	293
Los Angeles-Long Beach-Anaheim, CA	135	32	110	137	153
Chicago-Naperville-Elgin, IL-IN-WI	111	31	81	115	126
San Francisco-Oakland-Hayward, CA	107	35	74	105	130
Boston-Cambridge-Newton, MA-NH	107	42	67	101	135
Houston-The Woodlands-Sugar Land, TX	103	21	83	98	117
Dallas-Fort Worth-Arlington, TX	92	22	77	88	101
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	85	23	67	84	100
San Jose-Sunnyvale-Santa Clara, CA	83	49	42	66	122
Washington-Arlington-Alexandria, DC-VA-MD-WV	70	15	59	68	77
Minneapolis-St. Paul-Bloomington, MN-WI	65	27	43	61	85
Atlanta-Sandy Springs-Roswell, GA	63	18	50	59	73
Miami-Fort Lauderdale-West Palm Beach, FL	56	21	41	50	70
Denver-Aurora-Lakewood, CO	52	11	45	48	58
Seattle-Tacoma-Bellevue, WA	46	13	37	44	54
San Diego-Carlsbad, CA	35	22	21	26	59
St. Louis, MO-IL	32	10	22	30	40
Phoenix-Mesa-Scottsdale, AZ	31	8	23	31	36
Detroit-Warren-Dearborn, MI	29	9	24	28	34
Bridgeport-Stamford-Norwalk, CT	29	11	21	26	34
Pittsburgh, PA	26	7	19	27	30
Baltimore-Columbia-Towson, MD	24	7	18	23	29
Cleveland-Elyria, OH	23	11	12	22	28
Cincinnati, OH-KY-IN	23	4	20	22	24
Portland-Vancouver-Hillsboro, OR-WA	21	10	11	19	29
Kansas City, MO-KS	19	5	15	18	23
Columbus, OH	18	4	15	17	21
Charlotte-Concord-Gastonia, NC-SC	18	3	15	18	20
Tampa-St. Petersburg-Clearwater, FL	18	4	15	17	20
Milwaukee-Waukesha-West Allis, WI	18	6	11	18	22
Richmond, VA	18	4	15	17	20
Salt Lake City, UT	17	6	13	17	21
Austin-Round Rock, TX	16	4	13	16	18
Nashville-Davidson--Murfreesboro--Franklin, TN	16	5	11	15	21
Indianapolis-Carmel-Anderson, IN	16	5	12	14	19
Boulder, CO	16	3	12	17	17
Las Vegas-Henderson-Paradise, NV	16	3	13	15	17
Hartford-West Hartford-East Hartford, CT	15	5	11	13	19
Birmingham-Hoover, AL	15	3	13	16	18
Orlando-Kissimmee-Sanford, FL	14	3	12	14	16
Rochester, NY	14	3	12	13	17
Oxnard-Thousand Oaks-Ventura, CA	14	3	11	14	16
New Haven-Milford, CT	14	2	13	14	15
Memphis, TN-MS-AR	13	3	10	13	15

Table 2 – (*Continued*)

	Number of Firms				
Metropolitan Statistical Area	Mean	Std. Dev.	P25	Median	P75
Raleigh, NC	12	2	11	12	14
Providence-Warwick, RI-MA	12	3	10	11	13
Louisville/Jefferson County, KY-IN	12	2	11	12	13
Worcester, MA-CT	12	2	10	11	14
Santa Maria-Santa Barbara, CA	12	2	10	11	14
Trenton, NJ	12	2	10	12	13
Oklahoma City, OK	12	2	11	11	13
San Antonio-New Braunfels, TX	12	2	10	11	12
Grand Rapids-Wyoming, MI	12	2	10	12	12
Jacksonville, FL	11	1	11	11	12
Tulsa, OK	11	1	10	11	12
Greensboro-High Point, NC	11	1	10	12	12
New Orleans-Metairie, LA	11	1	10	11	12
Riverside-San Bernardino-Ontario, CA	11	1	10	11	12
Omaha-Council Bluffs, NE-IA	11	1	10	10	12
Dayton, OH	11	1	10	11	11
Youngstown-Warren-Boardman, OH-PA	11	1	10	11	11
Akron, OH	10	1	10	10	11
Buffalo-Cheektowaga-Niagara Falls, NY	10	1	10	10	11
Albany-Schenectady-Troy, NY	10	0	10	10	10
Durham-Chapel Hill, NC	10	0	10	10	10
Greenville-Anderson-Mauldin, SC	10	0	10	10	10
Manchester-Nashua, NH	10	0	10	10	10
Lafayette, LA	10	NA	10	10	10

Table 3
Geographic Peer Effects in Management Earnings Forecasts

This table reports the results from linear probability models relating the likelihood that a firm provides an earnings forecast to the proportion of local non-industry peers that provide earnings forecasts for firms from 1999 to 2015. The dependent variable *Forecast* in models 1-4 is an indicator variable that is set to one if a firm issues at least one earnings forecast during a fiscal year and zero otherwise. $Forecast^{Non\text{-}Ind,\ Local}$ equals the fraction of firms operating in the same MSA but in a different industry that provide at least one earnings forecast during the fiscal year. Table 1 provides definitions of all other variables. All continuous variables have been standardized to have a mean of zero and a standard deviation of one to ease the interpretation of coefficient estimates. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable = $Forecast_{(t)}$			
	(1)	(2)	(3)	(4)
$Forecast^{Non\text{-}Ind,\ Local}_{(t\text{-}1)}$	0.027***	0.020***	0.020***	0.018***
	(4.32)	(3.54)	(3.86)	(3.55)
$Forecast^{Ind}_{(t\text{-}1)}$	0.146***	0.149***	0.074***	0.077***
	(23.97)	(24.62)	(7.18)	(7.95)
Ln(Market Capitalization)$_{(t\text{-}1)}$		0.025***		0.134***
		(3.09)		(13.10)
Loss Indicator$_{(t)}$		-0.124***		-0.037***
		(-14.93)		(-5.40)
Earnings Volatility$_{(t)}$		-0.017***		-0.012***
		(-5.42)		(-3.32)
Return Volatility$_{(t)}$		-0.008*		-0.015***
		(-1.92)		(-3.45)
Ln(Number Analysts)$_{(t\text{-}1)}$		0.095***		0.048***
		(14.89)		(8.05)
Institutional Ownership$_{(t\text{-}1)}$		0.058***		0.011*
		(10.11)		(1.72)
Book-to-Market$_{(t\text{-}1)}$		0.004		0.008*
		(1.01)		(1.79)
Industry HHI$_{(t\text{-}1)}$		-0.007		-0.010
		(-1.45)		(-1.23)
Ln(P.C. Labor Income)$_{(t\text{-}1)}$		0.015***		0.062***
		(2.71)		(3.73)
% Change in P.C. Labor Income$_{(t)}$		0.002		0.005
		(0.64)		(1.53)
Ln(# Firms in MSA)$_{(t\text{-}1)}$		-0.015***		-0.007
		(-2.88)		(-0.19)
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	Yes
MSA Fixed Effects	No	No	Yes	Yes
Observations	40,771	40,771	40,771	40,771
Adjusted R^2	0.079	0.220	0.533	0.552

Table 4
Instrumental Variables Analysis

This table reports results from two-stage least squares regressions relating the likelihood that a firm provides an earnings forecast to the proportion of local non-industry peers that provide earnings forecasts for firms from 1999 to 2015. *Forecast* is an indicator variable that is set to one if a firm issues at least one earnings forecast during a fiscal year and zero otherwise. *Forecast$^{Non\text{-}Ind,\ Local}$* equals the fraction of firms operating in the same MSA but in a different industry that provide at least one earnings forecast during the fiscal year. In the first stage regressions (models 1, 3, and 5), we regress *Forecast$^{Non\text{-}Ind,\ Local}$* on the instrumental variables and controls. The instrument *Expected Forecast$^{Non\text{-}Ind,\ Local}$* equals the expected fraction of firms operating in the same MSA but in a different industry that provide at least one earnings forecast during the fiscal year. To estimate this expectation, we first set the likelihood that each firm will provide an earnings forecast (*Expected Forecast*) to the fraction of firms in the same industry but different MSA that provide at least one earnings forecast. We then average *Expected Forecast* across all firms in the same MSA but different industry as the firm of interest. The instrument *Avg. Idio. Risk$^{Non\text{-}Ind,\ Local}$* equals the equal-weighted average idiosyncratic stock return volatility of firms operating in the same MSA but in a different industry. To estimate each firm's idiosyncratic return volatility, we first regress each firm's monthly stock returns on market returns in excess of the risk-free rate and the returns of an equal-weighted MSA-level portfolio in excess of the risk-free rate. The regression is estimated for each firm on a rolling annual basis using historical monthly returns data over the prior three years (we require firms to have at least 24 months of returns). We then define each firm's idiosyncratic risk as the standard deviation of the residuals from this regression. In the second stage regressions (models 2, 4, and 6), we regress *Forecast* on the fitted values of *Forecast$^{Non\text{-}Ind,\ Local}$* from models 1, 3, or 5. Control variables include *Ln(Market Capitalization)$_{(t\text{-}1)}$*, *Loss Indicator$_{(t)}$*, *Earnings Volatility$_{(t)}$*, *Return Volatility$_{(t)}$*, *Ln(Number Analysts)$_{(t\text{-}1)}$*, *Institutional Ownership$_{(t\text{-}1)}$*, *Book-to-Market$_{(t\text{-}1)}$*, *Industry HHI$_{(t\text{-}1)}$*, *Ln(P.C. Labor Income)$_{(t\text{-}1)}$*, *% Change in P.C. Labor Income$_{(t)}$*, and *Ln(# Firms in MSA)$_{(t\text{-}1)}$*. Table 1 provides definitions of all other variables. All continuous variables have been standardized to have a mean of zero and a standard deviation of one to ease the interpretation of coefficient estimates. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Forecast$^{Non\text{-}Ind,\ Local}_{(t\text{-}1)}$	Forecast$_{(t)}$	Forecast$^{Non\text{-}Ind,\ Local}_{(t\text{-}1)}$	Forecast$_{(t)}$	Forecast$^{Non\text{-}Ind,\ Local}_{(t\text{-}1)}$	Forecast$_{(t)}$
	(1)	(2)	(3)	(4)	(5)	(6)
Expected Forecast$^{Non\text{-}Ind,\ Local}_{(t\text{-}1)}$	0.724***				0.681***	
	(30.34)				(29.39)	
Avg. Idio. Risk$^{Non\text{-}Ind,\ Local}_{(t\text{-}1)}$			-0.384***		-0.372***	
			(-28.80)		(-30.05)	
Fitted Forecast$^{Non\text{-}Ind,\ Local}_{(t\text{-}1)}$		0.064***		0.074***		0.071***
		(3.15)		(3.25)		(4.38)
Forecast$^{Ind}_{(t\text{-}1)}$	0.031**	0.086***	-0.162***	0.087***	0.042***	0.087***
	(2.11)	(8.21)	(-10.80)	(8.27)	(2.85)	(8.38)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,445	39,445	36,881	36,881	36,881	36,881
Adjusted R^2	0.766	0.551	0.764	0.564	0.782	0.564

Table 5
Effect of Local Institutional Investors

This table reports the results from linear probability models relating the likelihood that a firm provides an earnings forecast to the proportion of local non-industry peers that provide earnings forecasts for firms from 1999 to 2015. The dependent variable *Forecast* in models 1-5 is an indicator variable that is set to one if a firm issues at least one earnings forecast during a fiscal year and zero otherwise. $Forecast^{Non\text{-}Ind,\ Local}$ equals the fraction of firms operating in the same MSA but in a different industry that provide at least one earnings forecast during the fiscal year. *# of IO* is the number of institutional investors located in the same MSA as a firm. *$ of IO* is the total dollar holdings of all institutional investors located in the same MSA as a firm. *# of Existing IO* is the number of institutional investors located in the same MSA as a firm that are invested in the firm. *$ of Existing IO* is the total dollar holdings of all institutional investors located in the same MSA as a firm that are invested in the firm. *Existing % IO* is the fraction of shares owned by institutional investors located in the same MSA as the firm. Control variables include $Ln(Market\ Capitalization)_{(t\text{-}1)}$, $Loss\ Indicator_{(t)}$, $Earnings\ Volatility_{(t)}$, $Return\ Volatility_{(t)}$, $Ln(Number\ Analysts)_{(t\text{-}1)}$, $Institutional\ Ownership_{(t\text{-}1)}$, $Book\text{-}to\text{-}Market_{(t\text{-}1)}$, $Industry\ HHI_{(t\text{-}1)}$, $Ln(P.C.\ Labor\ Income)_{(t\text{-}1)}$, $\%\ Change\ in\ P.C.\ Labor\ Income_{(t)}$, and $Ln(\#\ Firms\ in\ MSA)_{(t\text{-}1)}$. Model 3 also controls for the natural logarithm of one plus the total number of institutional investors that are invested in the firm. Model 4 also controls for the natural logarithm of one plus the total dollar holdings of institutional investors that are invested in the firm. Table 1 provides definitions of all other variables. All continuous variables have been standardized to have a mean of zero and a standard deviation of one to ease the interpretation of coefficient estimates. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable = $Forecast_{(t)}$				
	(1)	(2)	(3)	(4)	(5)
$Forecast^{Non\text{-}Ind,\ Local}_{(t\text{-}1)}$	0.021***	0.020***	0.020***	0.019***	0.020***
	(3.96)	(3.75)	(3.85)	(3.78)	(3.84)
$Forecast^{Non\text{-}Ind,\ Local}_{(t\text{-}1)} \times Ln(\#\ of\ IO + 1)_{(t\text{-}1)}$	0.008**				
	(2.17)				
$Ln(\#\ of\ IO + 1)_{(t\text{-}1)}$	-0.059**				
	(-1.98)				
$Forecast^{Non\text{-}Ind,\ Local}_{(t\text{-}1)} \times Ln(\$\ of\ IO + 1)_{(t\text{-}1)}$		0.004			
		(1.26)			
$Ln(\$\ of\ IO + 1)_{(t\text{-}1)}$		0.014			
		(0.68)			
$Forecast^{Non\text{-}Ind,\ Local}_{(t\text{-}1)} \times Ln(\#\ of\ Existing\ IO + 1)_{(t\text{-}1)}$			0.007**		
			(2.10)		
$Ln(\#\ of\ Existing\ IO + 1)_{(t\text{-}1)}$			0.012		
			(1.18)		
$Forecast^{Non\text{-}Ind,\ Local}_{(t\text{-}1)} \times Ln(\$\ of\ Existing\ IO + 1)_{(t\text{-}1)}$				0.007**	
				(2.23)	
$Ln(\$\ of\ Existing\ IO + 1)_{(t\text{-}1)}$				-0.001	
				(-0.16)	
$Forecast^{Non\text{-}Ind,\ Local}_{(t\text{-}1)} \times Existing\ \%\ IO_{(t\text{-}1)}$					0.007*
					(1.87)
$Existing\ \%\ IO_{(t\text{-}1)}$					-0.003
					(-0.44)
$Forecast^{Ind}_{(t\text{-}1)}$	0.078***	0.078***	0.078***	0.078***	0.078***
	(8.00)	(7.96)	(8.04)	(8.03)	(8.00)
Control Variables	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	40,771	40,771	40,771	40,771	40,771
Adjusted R^2	0.552	0.552	0.552	0.552	0.552

Table 6
Geographic Peer Effects and Capital Market Consequences

This table reports the results from OLS regressions relating measures of a firm's stock liquidity to the proportion of local non-industry peers that provide an earnings forecast for firms from 1999 to 2015. The dependent variables in models 1-4 capture the illiquidity of a firm's stock and are defined as follows: *Illiquidity* follows Amihud (2002) and is defined as *AvgIlliq*$\times 10^9$, where *AvgIlliq* is the absolute value of daily returns divided by the day's dollar trading volume averaged over the firm's fiscal year; *Bid-Ask Spread* is the daily closing bid-ask spread scaled by the midpoint of the closing bid-ask spread averaged over the firm's fiscal year; *$ Trading Vol* is the daily dollar trading volume averaged over the firm's fiscal year; *Share Turnover* is the daily number of shares traded scaled by the number of shares outstanding averaged over the firm's fiscal year. *Forecast* is an indicator variable that is set to one if a firm issues at least one earnings forecast during a fiscal year and zero otherwise. $Forecast^{Non\text{-}Ind,\ Local}$ equals the fraction of firms operating in the same MSA but in a different industry that provide at least one earnings forecast during the fiscal year. Table 1 provides definitions of all other variables. All continuous control variables have been standardized to have a mean of zero and a standard deviation of one to ease the interpretation of coefficient estimates. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	$Ln(Illiquidity)_{(t)}$	Ln(Bid-Ask $Spread)_{(t)}$	–1×Ln($ Trading $Vol)_{(t)}$	–1×Ln(Share $Turnover)_{(t)}$
	(1)	(2)	(3)	(4)
$Forecast^{Non\text{-}Ind,\ Local}_{(t-1)}$	0.056***	0.081***	0.050***	0.029***
	(5.02)	(8.12)	(4.99)	(3.73)
$Forecast^{Non\text{-}Ind,\ Local}_{(t-1)} \times Forecast_{(t)}$	-0.029***	-0.019**	-0.026***	-0.015**
	(-2.87)	(-2.09)	(-2.81)	(-2.14)
$Forecast_{(t)}$	-0.059***	-0.019	-0.052***	-0.048***
	(-4.25)	(-1.57)	(-4.06)	(-5.03)
$Forecast^{Ind}_{(t-1)}$	0.053***	0.073***	0.074***	0.054***
	(3.14)	(4.43)	(4.83)	(4.45)
Ln(Market $Capitalization)_{(t-1)}$	-2.060***	-0.895***	-1.728***	-0.299***
	(-95.45)	(-44.23)	(-89.73)	(-19.05)
Loss $Indicator_{(t)}$	0.323***	0.153***	0.328***	0.108***
	(21.66)	(14.84)	(23.98)	(10.70)
Earnings $Volatility_{(t)}$	0.036***	0.016**	0.019**	0.006
	(4.03)	(2.49)	(2.41)	(1.06)
Return $Volatility_{(t)}$	0.202***	0.079***	-0.317***	-0.375***
	(18.40)	(9.89)	(-30.38)	(-51.02)
Ln(Number $Analysts)_{(t-1)}$	-0.099***	-0.001	-0.038***	-0.044***
	(-8.31)	(-0.13)	(-3.38)	(-4.79)
Institutional $Ownership_{(t-1)}$	-0.214***	-0.044***	-0.141***	-0.185***
	(-16.07)	(-4.04)	(-11.93)	(-18.61)
$Book\text{-}to\text{-}Market_{(t-1)}$	0.028***	-0.004	0.031***	0.066***
	(2.94)	(-0.58)	(3.70)	(9.44)
Industry $HHI_{(t-1)}$	-0.028**	-0.044***	-0.017	-0.021**
	(-2.17)	(-3.69)	(-1.44)	(-2.17)
Ln(P.C. Labor $Income)_{(t-1)}$	0.009	0.025	0.049*	0.058**
	(0.32)	(0.83)	(1.79)	(2.56)
% Change in P.C. Labor $Income_{(t)}$	-0.045***	-0.010**	-0.037***	-0.012***
	(-7.43)	(-2.17)	(-6.46)	(-2.86)
Ln(# Firms in $MSA)_{(t-1)}$	0.087	-0.065	0.034	-0.036
	(1.20)	(-0.92)	(0.53)	(-0.68)
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes
Observations	40,771	40,771	40,771	40,771
Adjusted R^2	0.947	0.895	0.928	0.732

Table 7
Effect of the Local Firm Density

This table reports the results from linear probability models relating the likelihood that a firm provides an earnings forecast to the proportion of local non-industry peers that provide earnings forecasts for firms from 1999 to 2015. The dependent variable *Forecast* in models 1-3 is an indicator variable that is set to one if a firm issues at least one earnings forecast during a fiscal year and zero otherwise. $Forecast^{Non\text{-}Ind,\ Local}$ equals the fraction of firms operating in the same MSA but in a different industry that provide at least one earnings forecast during the fiscal year. *Density* is the measure of non-industry local firm density defined in Section 4.3.2. Eq. (3). *VW Distance* is the value-weighted distance of all firms operating in the same MSA but in a different industry, in which weights are based on market capitalization. *# Non-Ind Local Firms* is the number of firms operating in the same MSA but in a different industry. Control variables include $Ln(Market\ Capitalization)_{(t\text{-}1)}$, $Loss\ Indicator_{(t)}$, $Earnings\ Volatility_{(t)}$, $Return\ Volatility_{(t)}$, $Ln(Number\ Analysts)_{(t\text{-}1)}$, $Institutional\ Ownership_{(t\text{-}1)}$, $Book\text{-}to\text{-}Market_{(t\text{-}1)}$, $Industry\ HHI_{(t\text{-}1)}$, $Ln(P.C.\ Labor\ Income)_{(t\text{-}1)}$, $\%\ Change\ in\ P.C.\ Labor\ Income_{(t)}$, and $Ln(\#\ Firms\ in\ MSA)_{(t\text{-}1)}$. Table 1 provides definitions of all other variables. All continuous variables have been standardized to have a mean of zero and a standard deviation of one to ease the interpretation of coefficient estimates. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable = $Forecast_{(t)}$		
	(1)	(2)	(3)
$Forecast^{Non\text{-}Ind,\ Local}_{(t\text{-}1)}$	0.019***	0.018***	0.019***
	(3.68)	(3.59)	(3.26)
$Forecast^{Non\text{-}Ind,\ Local}_{(t\text{-}1)} \times Ln(Density)_{(t\text{-}1)}$	0.001		
	(0.57)		
$Ln(Density)_{(t\text{-}1)}$	-0.007**		
	(-2.06)		
$Forecast^{Non\text{-}Ind,\ Local}_{(t\text{-}1)} \times Ln(VW\ Distance)_{(t\text{-}1)}$		0.001	
		(0.18)	
$Ln(VW\ Distance)_{(t\text{-}1)}$		0.001	
		(0.14)	
$Forecast^{Non\text{-}Ind,\ Local}_{(t\text{-}1)} \times Ln(\#\ Non\text{-}Ind\ Local\ Firms)_{(t\text{-}1)}$			0.004
			(1.25)
$Ln(\#\ Non\text{-}Ind\ Local\ Firms)_{(t\text{-}1)}$			-0.041
			(-1.59)
$Forecast^{Ind}_{(t\text{-}1)}$	0.078***	0.077***	0.079***
	(7.96)	(7.96)	(8.15)
Control Variables	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes
Observations	40,771	40,771	40,771
Adjusted R^2	0.550	0.552	0.552

Table 8
Effect of Shared Managers, Board Members, Analysts, and Institutional Investors

This table reports the results from linear probability models relating the likelihood that a firm provides an earnings forecast to the proportion of local non-industry peers that provide earnings forecasts for firms from 1999 to 2015. The dependent variable *Forecast* in models 1-5 is an indicator variable that is set to one if a firm issues at least one earnings forecast during a fiscal year and zero otherwise. $\textit{Forecast}^{\textit{Non-Ind, Local}}$ equals the fraction of firms operating in the same MSA but in a different industry that provide at least one earnings forecast during the fiscal year. In models 1 and 2, the sample of firms and geographic peer firms is restricted to those firms that can be matched to the Boardex database. In model 1, $\textit{Forecast}^{\textit{Non-Ind, Local}}$ is calculated after excluding geographic peers that have a board member who is also CEO of the firm. In model 2, $\textit{Forecast}^{\textit{Non-Ind, Local}}$ is calculated after excluding geographic peers that have a board member who also holds a management or board position at the firm. In model 3, $\textit{Forecast}^{\textit{Non-Ind, Local}}$ is calculated after excluding geographic peers that are covered by an analyst who also covers the firm. In models 4 and 5, $\textit{Forecast}^{\textit{Non-Ind, Local}}$ is calculated after excluding geographic peers in which an important institutional investor in the firm is also an important institutional investor of the peer firm. Important institutional investors are those that own at least 5% or 3% of the firms' outstanding shares in models 4 and 5, respectively. Control variables include *Ln(Market Capitalization)*$_{(t-1)}$, *Loss Indicator*$_{(t)}$, *Earnings Volatility*$_{(t)}$, *Return Volatility*$_{(t)}$, *Ln(Number Analysts)*$_{(t-1)}$, *Institutional Ownership*$_{(t-1)}$, *Book-to-Market*$_{(t-1)}$, *Industry HHI*$_{(t-1)}$, *Ln(P.C. Labor Income)*$_{(t-1)}$, *% Change in P.C. Labor Income*$_{(t)}$, and *Ln(# Firms in MSA)*$_{(t-1)}$. Table 1 provides definitions of all other variables. All continuous variables have been standardized to have a mean of zero and a standard deviation of one to ease the interpretation of coefficient estimates. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable = Forecast$_{(t)}$				
	Drop Shared CEO	Drop Shared Manager or Board Member	Drop Shared Analyst	Drop Shared IO – 5%	Drop Shared IO – 3%
	(1)	(2)	(3)	(4)	(5)
$\text{Forecast}^{\text{Non-Ind, Local}}_{(t-1)}$	0.012**	0.011**	0.013***	0.016***	0.014***
	(2.31)	(2.09)	(2.79)	(3.24)	(2.96)
$\text{Forecast}^{\text{Ind}}_{(t-1)}$	0.067***	0.065***	0.079***	0.080***	0.080***
	(4.79)	(4.74)	(7.96)	(8.07)	(8.01)
Control Variables	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	28,105	28,885	39,848	39,284	39,284
Adjusted R^2	0.669	0.669	0.554	0.556	0.556

Table 9
Robustness: Alternative Industry Definitions

This table reports the results from linear probability models relating the likelihood that a firm provides an earnings forecast to the proportion of local non-industry peers that provide earnings forecasts for firms from 1999 to 2015. The dependent variable *Forecast* in models 1-5 is an indicator variable that is set to one if a firm issues at least one earnings forecast during a fiscal year and zero otherwise. $Forecast^{Non\text{-}Ind,\ Local}$ equals the fraction of firms operating in the same MSA but in a different industry that provide at least one earnings forecast during the fiscal year. In model 1, firms are grouped into 25 separate industries using the 10-K text-based fixed industry classifications from Hoberg and Phillips (2010, 2016). In model 2, industries are defined by two-digit SIC codes. In models 3-5, industries are defined by the Fama-French 12, 17, and 49 industry classifications, respectively. For each industry classification, we require that both portfolios $Forecast^{Non\text{-}Ind,\ Local}$ and $Forecast^{Ind}$ be calculated using at least 10 firms, resulting in different sample sizes from our main tests and across the specifications. Control variables include *Ln(Market Capitalization)*$_{(t-1)}$, *Loss Indicator*$_{(t)}$, *Earnings Volatility*$_{(t)}$, *Return Volatility*$_{(t)}$, *Ln(Number Analysts)*$_{(t-1)}$, *Institutional Ownership*$_{(t-1)}$, *Book-to-Market*$_{(t-1)}$, *Industry HHI*$_{(t-1)}$, *Ln(P.C. Labor Income)*$_{(t-1)}$, *% Change in P.C. Labor Income*$_{(t)}$, and *Ln(# Firms in MSA)*$_{(t-1)}$. Table 1 provides definitions of all other variables. All continuous variables have been standardized to have a mean of zero and a standard deviation of one to ease the interpretation of coefficient estimates. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable = $Forecast_{(t)}$				
	HP25	SIC2	FF12	FF17	FF49
	(1)	(2)	(3)	(4)	(5)
$Forecast^{Non\text{-}Ind,\ Local}_{(t-1)}$	0.015***	0.018***	0.017***	0.016***	0.017***
	(3.00)	(3.48)	(3.23)	(3.15)	(3.24)
$Forecast^{Ind}_{(t-1)}$	0.056***	0.087***	0.082***	0.080***	0.084***
	(9.26)	(11.97)	(8.49)	(8.99)	(11.17)
Control Variables	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	41,160	40,880	41,506	41,033	41,015
Adjusted R^2	0.548	0.553	0.550	0.553	0.551

Table 10
Robustness: Data Frequency and Model Specification

This table reports the results from models relating the likelihood that a firm provides an earnings forecast to the proportion of local non-industry peers that provide earnings forecasts for firms from 1999 to 2015. The dependent variable *Forecast* in models 1-5 is an indicator variable that is set to one if a firm issues at least one earnings forecast during a fiscal year (or quarter) and zero otherwise. Model 1 estimates a linear probability model using quarterly data, and *Forecast$^{Non\text{-}Ind,\ Local}$* equals the fraction of firms operating in the same MSA but in a different industry that provide at least one earnings forecast during the fiscal quarter. For this test, we limit our sample to quarterly forecasts, and variables in *t*-1 are measured in the prior quarter. Models 2-5 use annual data, and *Forecast$^{Non\text{-}Ind,\ Local}$* equals the fraction of firms operating in the same MSA but in a different industry that provide at least one earnings forecast during the fiscal year. Model 2 controls for *Forecast* in year *t-1*. Model 3 includes only point and range earnings forecasts. In model 4, we first determine the predicted values of *Forecast* by estimating model 4 of Table 3. Next, we re-estimate this regression after dropping any observation in which the predicted value of *Forecast* is outside the [0, 1] interval. Model 5 estimates a conditional logistic regression. The sample size decreases from 40,771 to 24,702 observations because the conditional logistic model drops firms that either provide a forecast every year over the sample period or never provide a forecast over the sample period. Model 6 uses our main sample from model 4 of Table 3 and reports the results from an OLS regression relating the frequency that a firm provides an earnings forecast to the average forecast frequency of local non-industry peers. The dependent variable *Ln(Freq+1)* is the natural logarithm of one plus the number of earnings forecasts a firm provides during a fiscal year. *Ln(Freq+1)$^{Non\text{-}Ind,\ Local}$* is the average of the natural logarithm of one plus the number of earnings forecasts made by firms operating in the same MSA but in a different industry during a fiscal year. *Ln(Freq+1)^{Ind}* is the average of the natural logarithm of one plus the number of earnings forecasts made by firms in the same industry (the firm itself is excluded from the calculation). Control variables include *Ln(Market Capitalization)$_{(t-1)}$, Loss Indicator$_{(t)}$, Earnings Volatility$_{(t)}$, Return Volatility$_{(t)}$, Ln(Number Analysts)$_{(t-1)}$, Institutional Ownership$_{(t-1)}$, Book-to-Market$_{(t-1)}$, Industry HHI$_{(t-1)}$, Ln(P.C. Labor Income)$_{(t-1)}$, % Change in P.C. Labor Income$_{(t)}$*, and *Ln(# Firms in MSA)$_{(t-1)}$*. Table 1 provides definitions of all other variables. All continuous variables have been standardized to have a mean of zero and a standard deviation of one to ease the interpretation of coefficient estimates. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable = Forecast$_{(t)}$					Ln(Freq +1)$_{(t)}$
	Quarterly Data (1)	Lagged Dep. Var. (2)	Point and Range (3)	Trimmed (4)	Conditional Logistic (5)	(6)
Forecast$^{Non\text{-}Ind,\ Local}_{(t-1)}$	0.009**	0.014***	0.021***	0.017***	0.163***	
	(2.44)	(3.39)	(3.84)	(3.33)	(3.74)	
Forecast$^{Ind}_{(t-1)}$	0.069***	0.051***	0.082***	0.076***	0.552***	
	(11.42)	(6.41)	(7.99)	(7.77)	(7.07)	
Forecast$_{(t-1)}$		0.259***				
		(31.92)				
Ln(Freq + 1)$^{Non\text{-}Ind,\ Local}_{(t-1)}$						0.032***
						(2.89)
Ln(Freq + 1)$^{Ind}_{(t-1)}$						0.186***
						(10.47)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes	No	Yes
Observations	153,045	40,420	40,771	39,017	24,702	40,771
Adjusted R^2 (Wald χ^2)	0.471	0.586	0.561	0.548	(932.6)	0.610

Table 11
Effect of Excluding Prominent Geographic Areas

This table reports the results from linear probability models relating the likelihood that a firm provides an earnings forecast to the proportion of local non-industry peers that provide earnings forecasts for firms from 1999 to 2015. The dependent variable *Forecast* in models 1-6 is an indicator variable that is set to one if a firm issues at least one earnings forecast during a fiscal year and zero otherwise. $Forecast^{Non\text{-}Ind,\ Local}$ equals the fraction of firms operating in the same MSA but in a different industry that provide at least one earnings forecast during the fiscal year. Models 1-3 exclude any firm headquartered in California, Texas, and New York, respectively. Model 4 excludes any firm headquartered in either California, Texas, or New York. Models 5 and 6 exclude any firm headquartered in one of the five or ten largest MSAs (based on the number of firms in our sample headquartered in the MSAs). Control variables include $Ln(Market\ Capitalization)_{(t-1)}$, $Loss\ Indicator_{(t)}$, $Earnings\ Volatility_{(t)}$, $Return\ Volatility_{(t)}$, $Ln(Number\ Analysts)_{(t-1)}$, $Institutional\ Ownership_{(t-1)}$, $Book\text{-}to\text{-}Market_{(t-1)}$, $Industry\ HHI_{(t-1)}$, $Ln(P.C.\ Labor\ Income)_{(t-1)}$, $\%\ Change\ in\ P.C.\ Labor\ Income_{(t)}$, and $Ln(\#\ Firms\ in\ MSA)_{(t-1)}$. Table 1 provides definitions of all other variables. All continuous variables have been standardized to have a mean of zero and a standard deviation of one to ease the interpretation of coefficient estimates. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable = $Forecast_{(t)}$					
	Drop CA	Drop TX	Drop NY	Drop CA, TX, NY	Drop 5 Largest MSAs	Drop 10 Largest MSAs
	(1)	(2)	(3)	(4)	(5)	(6)
$Forecast^{Non\text{-}Ind,\ Local}_{(t-1)}$	0.015***	0.018***	0.018***	0.016***	0.013**	0.016***
	(2.79)	(3.51)	(3.56)	(2.78)	(2.41)	(2.71)
$Forecast^{Ind}_{(t-1)}$	0.073***	0.069***	0.078***	0.060***	0.075***	0.076***
	(6.94)	(6.33)	(7.69)	(4.69)	(6.41)	(4.99)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,031	36,676	37,188	24,353	25,476	16,539
Adjusted R^2	0.557	0.553	0.549	0.555	0.550	0.544