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The Internet and Local Wages: A Puzzle†

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US businesses made substantial investments in the Internet in the 1990s. A growing body of evidence suggests the Internet lowered the costs of engaging in economic activity in geographically isolated locations.[1] In addition, research shows information technology (IT)–using industries, firms, and locations experienced exceptionally good economic performance.[2] Yet, no study traces the relationship between regional growth and Internet investment. This study contributes new statistical evidence to this topic and frames a puzzle. We find that while the Internet is widespread, the payoffs are not.

To establish this, we present novel data about the association between Internet investment and county-level wage growth from 1995 to 2000. This was the period of initial and rapid investment in the Internet by business. As in our prior research (Forman, Goldfarb, and Greenstein 2005), we look beyond the diffusion of e-mail and web browsing, focusing on the diffusion of advanced Internet applications. These investments enabled productivity advances due to lower costs of communicating with suppliers and customers over long distances and required skilled labor to implement and operate.

We find that investment in the Internet is correlated with wage and employment growth in only about 6 percent of US counties, representing 42 percent of the US population. These counties were already well off prior to 1995, with high income, large populations, high skills, and concentrated information technology (IT) use. These well-off counties averaged 28 percent wage growth from 1995 to 2000 (unweighted by population), while all counties averaged just 20 percent wage growth over this period. We show that the Internet exacerbates regional wage inequality,

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[1] Prior work (Forman, Goldfarb, and Greenstein 2005) showed that basic Internet use was disproportionately adopted by businesses in low-density areas. Furthermore, lower communication costs have enabled the delivery of a set of tradable services at a distance from the point of final demand (Arora and Gambardella 2005; Organization for Economic Cooperation and Development (OECD) 2006).

[2] This holds whether performance is measured at the national (Jorgenson, Ho, and Stiroh 2005), city (Beaudry, Doms, and Lewis 2006; Kolko 2002), industry (Stiroh 2002), firm (Brynjolfsson and Hitt 2003), or establishment (Bloom, Sadun, and Van Reenen 2007) levels.

explaining over half the *additional* wage growth experienced by the 6 percent of counties that were already well off. A large battery of analyses and tests suggests a causal relationship.

We establish the results in steps. First, we find a statistically significant but economically small positive correlation between advanced Internet investment and local wage growth. This correlation remains robust to numerous specifications and controls. Next we provide evidence that advanced Internet contributes to regional wage divergence: the relationship between advanced Internet investment and local wage growth is primarily found in the 163 counties that, as of 1990, had a population over 150,000 and were in the top quartile in income, education, and fraction of firms in IT-intensive industries.

We focus on these four factors because of existing theory and evidence that they influence the relationship between IT investments, productivity, and labor market outcomes. We focus on population because larger cities had thicker labor markets for complementary services, specialized skills, or specialized vendors that have the potential to increase the productivity of IT investments. We focus on education because considerable evidence points towards complementarities between the use of advanced information technology and a skilled labor force, and focus on income as both a proxy for skills and a way to examine whether Internet technology exacerbated existing inequality. We focus on IT intensity because Internet technology complemented existing IT installations by facilitating data communication.

The results highlight *what happened* in 6 percent of counties, and *what did not* happen in the other 94 percent. This is the payoff puzzle: only a few counties experienced wage growth, despite widespread Internet investment.

We address the assumption that Internet investment is exogenous. First, we control for many factors known to shape investment decisions, and the results do not change. Second, we instrument for advanced Internet in three ways. One, the Bartik procedure, is familiar to the literature in labor economics. The other two are tailored to our setting, taking advantage of features of the cost structure for Internet technology. Third, we show that the timing of regional wage divergence is strongly associated with the timing of the diffusion of the business Internet. The strong association between Internet adoption and growth for those 163 counties that were already doing well starts in 1996, after the diffusion of the Internet.

A scatterplot of the raw data forecasts our core results. Figure 1 panel A shows the relationship between advanced Internet investment and local wage growth for all types of counties in the raw data. While the regression line is upward sloping (it is also significantly positive), advanced Internet does not explain much of the variation in wage growth. In contrast, Figure 1 panel B compares all counties to the 163 counties that were already doing well (i.e., counties with high income, population, education, and agglomeration of IT-intensive firms). In these 163 counties advanced Internet is strongly correlated with wage growth; for the other counties, there is no relationship between advanced Internet and wage growth despite many having made substantial investments.[3]

[3] Figure 1 truncates the picture, removing counties with extreme Internet use. The results are qualitatively similar.

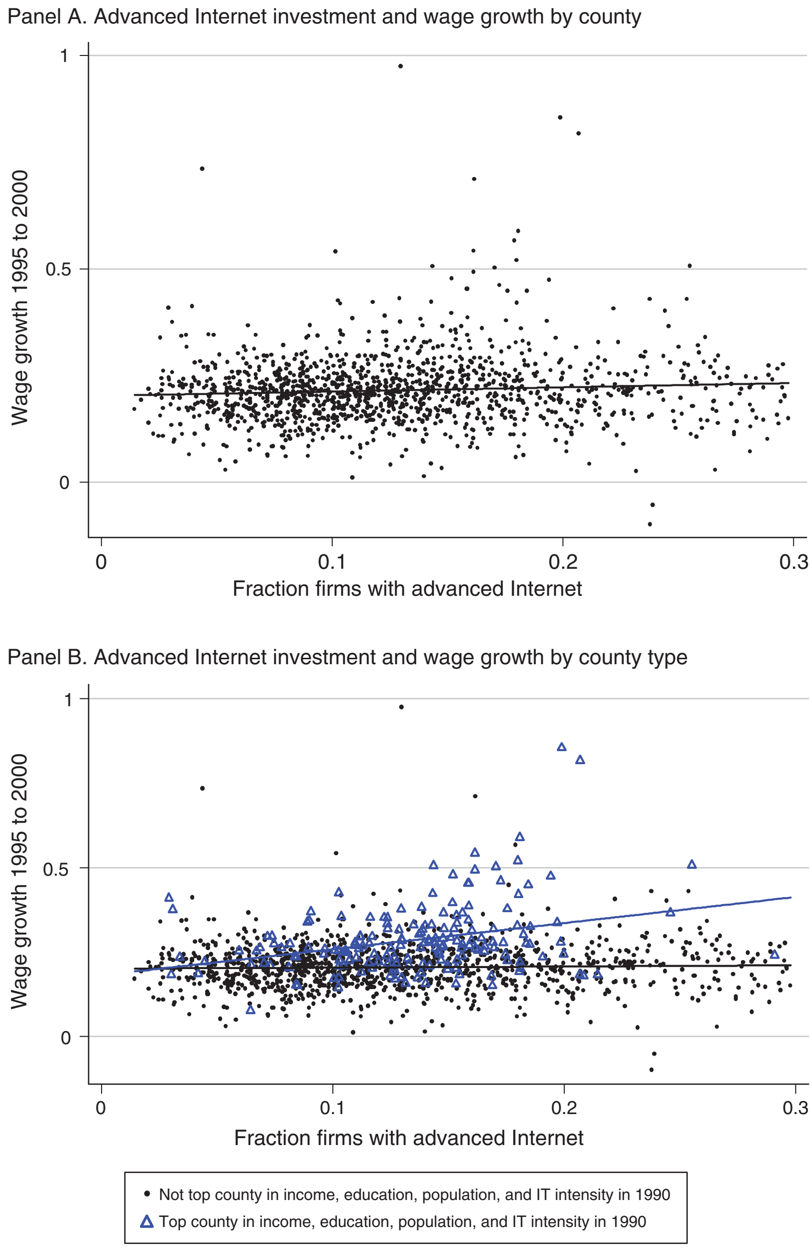

Figure 1. Advanced Internet Investment and Wage Growth by County and County Type

This puzzle speaks to a large literature about regional growth.[4] We differ from work focused on regional prosperity of agglomerated IT producers, such as Santa

[4] Magrini (2004) provides a survey on the causes of convergence/divergence across regions. Glaeser and Ponzetto (2007) argue that low communication costs help rich, idea-producing areas more than poor, goods-producing areas. They do not empirically focus on IT but show that the share of skilled occupations increases with local wage growth. Also related are Glaeser et al. (1992), Barro and Sala-i-Martin (1991), and Higgins, Levy, and Young (2006).

Clara and Boston. Rather, we focus on economic growth from use of the Internet, which spread quickly by 2000. Our results are also inconsistent with popular optimism about the economic promise of a widely deployed Internet (e.g., Cairncross 1997; Friedman 2005). We do not find any evidence of improvement in the *comparative* economic performance of isolated locations or less dense locations. The Internet may have allowed firms in rural Iowa to reach new customers, just as it allowed Wall Street banks to reach investors in rural Iowa. Yet, the findings show an increase in wages in New York City and not Iowa.

Our findings of inequality in wage growth suggest that Internet technology followed the skill-biased pattern observed with previous generations of IT.[5] However, that alone does not explain the puzzle. A highly educated labor force is insufficient for a location to realize wage gains. Other factors also shape local labor markets, coincident with local population size, industry composition, and income. The combination of all of these factors, and the fact that many places without these factors adopted but did not benefit, frames the payoff puzzle.

Our results have important public policy implications. A wide array of policies subsidizing Internet infrastructure in low density locations have arisen since the diffusion of the Internet. Our results suggest infrastructure growth has little impact without appropriate supply of skilled labor. Yet, most infrastructure subsidies include little or no provision for developing the human capital required to employ advanced IT. In addition, we find little economic impact from the Internet on wages in low density areas, suggesting such policies might have limited local impact even if both human and physical capital received subsidies.

I. Measuring the Localization of Growth

Our statistical approach proceeds in two broad steps. We first measure the average relationship between Internet use and wage growth across all counties. Then, we establish the payoff puzzle by examining where advanced Internet investment led to faster growth.

Step 1. Advanced Internet and Local Wage Growth.—We compare the wages of a time period before advanced Internet technologies diffused (1995) to those of a period when we observe use (2000). We take advantage of the fact that many local features that shaped labor markets and enterprises in 1995 had not changed by 2000. Our endogenous variable will be the log difference in wages between 1995 and 2000, yielding:

$$\log(Y_{i00}) - \log(Y_{i95}) = \alpha X_i + \beta Internet_i + \varepsilon_i. \tag{1}$$

Here, $Internet_i$ measures the extent of advanced Internet investment by businesses in location i in 2000. We have assumed that ε_i is a normal i.i.d. variable. We include two kinds of controls in X_i: controls for preexisting initial conditions that may affect

[5] An extensive literature examines wage inequality and skilled-biased technical change (e.g., Katz and Autor 1999), and how the demand for computing has affected wage inequality (e.g., Autor, Levy, and Murnane 2003; Autor, Katz, and Kearney 2006).

wage growth such as income, population, and education levels, and controls for changes in the factors not directly related to income over time and for which we have data (see Table 1B for a complete list).

Our hypothesis is that increases in local business use of advanced Internet will be associated with growth in local wages: a test of $\beta > 0$ against the null of $\beta = 0$.

Step 2. Use of the Internet and the Payoff Puzzle.—We examine whether advanced Internet improved growth prospects in many regions or whether it was limited to a handful of places. We examine several aspects of local economies that may affect the relationship between advanced Internet investment and wages, specifically, income, skills (measured by education), population, and IT intensity. We focus on the extreme position that locations with the combination of these factors and income will exhibit the strongest relationship between advanced Internet and wage growth. We use this extreme position because it provides a way to simplify the five-way interaction. Those counties that score high on all factors are termed *HighAllFactors*. To investigate these comparative statics of our framework, we estimate the following:

$$\begin{aligned}(2)\quad \log(Y_{i00}) - \log(Y_{i95}) = {} & \alpha_1 X_i + \beta \mathit{Internet}_i \\ & + \phi_1(\mathit{Internet}_i \times \mathit{HighIncome}_i) \\ & + \phi_2(\mathit{Internet}_i \times \mathit{HighEducation}_i) \\ & + \phi_3(\mathit{Internet}_i \times \mathit{HighPopulation}_i) \\ & + \phi_4(\mathit{Internet}_i \times \mathit{HighITIntensity}_i) \\ & + \phi_5(\mathit{Internet}_i \times \mathit{HighAllFactors}_i) + \varepsilon_i.\end{aligned}$$

Here ϕ_5 measures differences between counties with *HighAllFactors* and other counties. If $\beta = 0$ and $\phi_1 = \phi_2 = \phi_3 = \phi_4 = 0$ but $\phi_5 > 0$, then the payoff to business Internet investment is isolated to locations with high income, education, population, and IT intensity. Such a finding also has implications for identification in the presence of potential omitted variables. If this result is a false positive caused by positive covariance between changes in ε_i and advanced internet investment, then it suggests this covariance is isolated only to a small minority of locations. While we cannot reject this possibility, we find it difficult to identify a specific economic mechanism that acts in just a limited number of places.

More generally, a potential concern in this econometric exercise is that unobservable changes to local firm or worker characteristics may be correlated with both wage growth and Internet use. We provide considerable suggestive evidence that, when combined, shows that advanced Internet investment is strongly correlated with local wage growth. First, as noted above, we include many controls for the initial conditions of the county to address omitted variables bias at the county level. Additionally, we include controls for changes in county characteristics such as population and age distribution as well as controls for changes in closely related margins of consumer and business IT investment (basic Internet investment, PCs per employee, and Internet use at home). If advanced Internet investment is associated with wage growth controlling for these other margins of IT investment, then omitted variable bias must be specific to advanced Internet.

Second, we present instrumental variables regressions that use measures of local telecommunications infrastructure costs, local industry, and the programming capabilities of related locations as instruments for local Internet investment. As we describe in greater detail below, changes in the values of these instruments will proxy for variance in the local costs of advanced Internet but are unlikely to be systematically correlated with local wage growth.

Finally, the Internet's sudden deployment gives us an additional test for the role of location-specific omitted variables: it enables us to employ a useful falsification test. We should not see any affiliation between Internet investment and the divergence of regional wages before 1995.[6] If our assumptions of the orthogonality between the Internet and changes in local unobservables are violated, then our data will produce false positive associations between future investment and regional wage divergence in a period prior to 1995. The absence of such false positives boosts confidence in our exogeneity assumptions.

II. Data

To measure how Internet investment influenced growth in wages, we combine several data sources about medium and large establishments and about US counties.[7] Our IT data come from the Harte Hanks Market Intelligence Computer Intelligence Technology database (also used in Bloom et al. 2009 and our own prior work). The database contains rich establishment- and firm-level data including the number of employees, personal computers per employee, and use of Internet applications. Harte Hanks collects this information to resell as a tool for the marketing divisions of technology companies. Interview teams survey establishments throughout the calendar year; our sample contains the most current information as of December 2000.

Harte Hanks tracks over 300,000 establishments in the United States. We exclude government, military, and nonprofit establishments because the availability of advanced Internet for these establishments and their relationship between adoption and labor demand is likely to be systematically different than for private establishments. For example, many military establishments had access to ARPANET as early as 1970. Our sample contains commercial establishments with over 100 employees—in total, 86,879 establishments.[8] While the sample includes only relatively large establishments, we do not view this as a problem because very few small

[6] Dating the rise of the commercial Internet is not an exact science, but a few well-known events provide useful benchmarks for understanding why investment began to boom in 1996 and not before. The first nonbeta version of the Netscape browser became available in early 1995, followed by the firm's IPO in August 1995. Bill Gates' internal memo about Microsoft's change in direction ("The Internet Tidal Wave") is dated May 1995. Certainly no serious vendor in IT markets was ignoring the commercial Internet by December 1995; after Microsoft's announcement of its change in strategy; neither was any large-scale investor in IT applications.

[7] This section contains an overview of our data. Further details on the construction of our measure of Internet investment and of our controls are available in the online Data Appendix.

[8] Establishments were surveyed at different times from June 1998 to December 2000. To control for increasing adoption rates, we reweight our adoption data by the ratio of average adoption rates in our sample between the month of the survey and the end of 2000.

establishments deployed advanced Internet technology at the time. The primary investors were large establishments making enterprisewide investments worth tens of millions of dollars, and, in some multiestablishment organizations, hundreds of millions of dollars per year.[9]

We focus on those facets of Internet technology that became available only after 1995 in a variety of different uses and applications. The raw data include at least 20 different specific applications, from basic access to software for Internet-enabled enterprise resource planning (ERP) business applications. Advanced Internet involves frontier technologies and significant adaptation costs. Substantial investments in e-commerce or e-business applications identify advanced Internet.[10]

We stress that the investments we consider include several aspects of an enterprise's operations, not just the most visible downstream interactions with customers. These often involve upstream communication with suppliers and/or new methods for organizing production, procurement, and sales practices. We look for commitment to two or more of the following Internet-based applications: ERP, customer service, education, extranet, publications, purchasing, or technical support. Most often, these technologies involve interestablishment communication and substantial changes to business processes. We experimented with alternative measures of business Internet use, and the results are qualitatively similar.

To obtain location-level measures of the extent of advanced Internet investment, we compute average rates of use for a location. Because the distribution of establishments over industries may be different in our sample from that of the population, we weight the number of establishments in our database using the number of establishments by two-digit North American Industry Classification System (NAICS) industry in the Census Bureau's 1999 County Business Patterns data.

Prior research has shown that this measure has several attractive properties. For example, when aggregated to the industry level, this measure positively correlates with Bureau of Economic Analysis measures of industry-level differences in IT investment, as we would expect. Examples of industries that tend to have high advanced Internet investment are Electronics Manufacturing, Automobile Manufacturing and Distribution, and Financial Services (Forman, Goldfarb, and Greenstein 2002). Yet, it captures more than just the industry, varying considerably across establishments in different firms and regions. Among the biggest cities, areas with high use are those where a high fraction of local employment is in Internet-intensive (as well as IT-intensive) industries, such as the San Francisco Bay Area, Seattle, Denver, and Houston (Forman, Goldfarb, and Greenstein 2005). In these places, use is relatively high even in industries that are not IT-intensive. Thus, both the industry composition and the features of local areas shape use in the direction that economic intuition would forecast.

We obtain county-level data about businesses on average weekly wages paid and total employment from the Quarterly Census of Employment and Wages, a cooperative program of the Bureau of Labor Statistics and the State Employment Security

[9] All our available evidence suggests that adoption monotonically increased in firm size, even controlling for many other determinants. Hence, our sample represents the vast majority of adopters.

[10] In previous work this was labeled *enhancement* because it enhanced existing IT processes and contrasted with *participation*; that is, the use of basic Internet technologies, such as e-mail or browsing (e.g., Forman, Goldfarb, and Greenstein 2002, 2005). In this article, the contrasts are not the central focus, so we call it *advanced Internet*.

Agencies. Matching these data to our Internet data leaves a total of 2,743 county observations. We drop about 10 percent of the total counties because we lack data on Internet investment. We retain almost every urban and suburban county, as well as most rural ones. The vast majority of the dropped counties come from the lowest quartile of the population distribution. Results are robust to using multiple imputation to deal with the missing data.

To examine whether the impact was limited to a narrow set of counties, we focus on the roles of *income*, *education*, *population*, and *IT intensity*. The data on *population*, *education*, and *income* come from the 1990 US Census. For IT intensity, we measure the fraction of firms in IT-using and IT-producing industries in the county as of 1995 from the US Census County Business Patterns data. National aggregate data show that such industries have unusually high returns from investment in IT in the 1990s. We define these industries using the classification reported in Jorgenson, Ho, and Stiroh (2005).[11]

We combine these data with county-level information from a variety of sources. This information allows us to control for the underlying propensity of the counties to grow and innovate. First, the 1990 US Census provides county-level information on population, median income, net migration to the county (from 1995 data), and the percentage of university graduates, high school graduates, African Americans, persons below the poverty line, and persons over age 65. We also use the 2000 US Census to control for changes in non–income-related factors: population, net migration to the county, and percentages of university graduates, high school graduates, persons over age 65, and African Americans. The 2000 Current Population Survey (CPS) Computer and Internet Use Supplement (also used in DiMaggio and Bonikowski 2008) provides our data on the percentage of households adopting the Internet at home. We use four measures of county-level propensity to innovate: (i) The number of students in Carnegie rank 1 research universities in 1990; (ii) The fraction of students enrolled in engineering programs; (iii) The percentage of the county's work force in professional occupations in 1990; and (iv) The number of patents granted in the 1980s in that county, as found in the NBER patent database.[12]

Table 1A includes descriptive statistics on IT use and our measures of local wages and employment. Table 1B includes a description of control variables.

III. Empirical Results

We initially establish a link between advanced Internet and wages and show that it differs from basic Internet and personal computers. We next present the main result that advanced Internet investment is associated with wage growth only in counties with high levels of income, education, population, and IT-intensity industry. Robustness checks and instrumental variables analysis follow, as does an analysis of

[11] These industries are Communications (SIC 48), Business Services (73), Wholesales Trade (50–51), Finance (60–62, 67), Printing and Publishing (27), Legal Services (81), Instruments and Miscellaneous Manufacturing (38–39), Insurance (63–64), Industrial Machinery and Computing Equipment (35), Gas Utilities (492, 496, and parts of 493), Professional and Social Services (832–839), Other Transportation Equipment (372–379), Other Electrical Machinery (36, ex. 366–267), Communications Equipment (SIC 366), and Electronic Components (367).

[12] Downes and Greenstein (2007) showed that the first three help explain availability of Internet service providers.

Table 1A—Descriptive Statistics for Dependent Variables, IT Measures, and Instruments (*for* 2000)

Variable	Mean	SD	Minimum	Maximum	Observations
Log(average weekly wage)	6.153	0.2189	5.4931	7.333	2,743
Log(employment)	9.190	1.4695	4.3175	15.08	2,743
Advanced Internet	0.0890	0.1332	0	1	2,743
Basic Internet	0.7869	0.4499	0	1	2,743
PCs per employee	0.2253	0.1719	0	1.937	2,743
Average number of programmers in other establishments in the same firm	47.32	70.09	0	1,137.6	2,743
Bartik index	0.1126	0.0216	0	0.2664	2,743
ARPANET connections	0.0215	0.2383	0	7	2,743
Average cost per phone line by state	24.06	3.92	14.92	36.42	2,743

Table 1B—Description of Control Variables

Variable	Definition	Source	Mean
Home Internet use	Percentage of households with internet at home (2000)	Current Population Survey (CPS) Internet Use Supplement (Census)	0.444
Home Internet data missing	Dummy indicating no data on home Internet use	Current Population Survey (CPS) Internet Use Supplement (Census)	0.9213
Total population	Total population as of Decennial Census (1990)	US Census	89,173
Percent African American	% population African American as of Decennial Census (1990)	US Census	0.0908
Percent university graduates	% population university graduates as of Decennial Census (1990)	US Census	0.1379
Percent high school graduates	Percent population high school graduates as of Decennial Census (1990)	US Census	0.6996
Percent below poverty line	Percent population below poverty line as of Decennial Census (1990)	US Census	0.1622
Median household income	Median county household income as of Decennial Census (1990)	US Census	24493
Enrolled in Carnegie rank 1 research university	Per capita number of students enrolled in local PhD-granting institutions	Downes-Greenstein (2007)	0.0081
In engineering program	Per capita number of students enrolled in engineering programs at local universities	Downes-Greenstein (2007)	0.0010
Patents granted in the county in the 1980s	Total number of patents from inventors located in county, 1980-1989	USPTO	155.7
Percent professional	% of county's work force employed in professional occupations	US Census	0.3258
Net migration	Net migration to county	US Census	123.5
% population over age 65	Percent of county population over 65 as of Decennial Census	US Census	0.1452

the timing of the relationship between Internet investment and wage growth. Finally, we explore some additional implications.

A. *Internet Investment and Average Wages*

In Table 2, we show the baseline results across counties. Column 1 shows the correlation between advanced Internet investment and wage growth at the county level without any controls. As suggested by the scatterplots in Figure 1, the correlation is significant and positive. Column 2 provides what we define as our main specification: Namely, it includes controls for levels of presample demographics (such as county population in 1990) and presample innovativeness. It also includes controls for changes in nonincome demographics (such as net migration from 1990 to 2000) and changes in home Internet adoption (effectively zero in 1995). The coefficient on advanced Internet is 0.0278. That is, regions with an average level of advanced Internet (8.9 percent) experienced wage growth 0.247 percentage points above that of regions with no Internet use. A one standard deviation increase in the use of the Internet is associated with a 0.370 percentage point increase in wage growth. The data are skewed, so it is also interesting to look at the top decile of advanced Internet, which is 21.6 percent. That leads to a 0.353 percentage point increase in wage growth above the mean. Consistent with Figure 1A, this suggests that advanced Internet was not the primary force behind the 20 percent wage growth across all counties in our data from 1995 to 2000.

Even with such a small coefficient, omitted variable bias is an important concern in this analysis. Below, after presenting our main results on regional variation in the relationship between wage growth and Internet investment, we use instruments and the timing of regional wage divergence to argue for a causal explanation of our results.

In column 3, we examine whether advanced Internet might proxy for other kinds of IT, such as basic Internet investment and PCs per employee (measured using the Harte Hanks database).[13] While PCs per employee appear positively correlated with wage growth, this relationship is not statistically significant. Furthermore, including other kinds of IT as controls does not substantially change the relationship between advanced Internet and wages. This suggests that advanced Internet investment is not simply a surrogate measure of IT intensity. Instead, the relationship between wage growth and advanced Internet is driven by variation in advanced Internet investment in particular.

The lack of correlation between basic Internet technologies (e.g., e-mail and browsing) and wage growth is surprising because levels of adoption were high across establishments and locations by 2000. Revealed preference therefore suggests the benefits were high, especially for a technology with so little use only five years earlier. We speculate that our intuition about revealed preference applies to an inframarginal adopter: when the technology is almost universally adopted, the data may be identifying an uninteresting margin.

[13] Forman, Goldfarb, and Greenstein (2005) use the same measure of basic Internet investment and show it was widely adopted by 2000. The measure of PCs per employee resembles that used by Beaudry, Doms, and Lewis (2006). See the online Appendix for details.

Table 2—Wages Increase with Internet Use

	No controls (1)	Full set of controls (2)	Include all three measures of IT use (3)
Advanced Internet	0.0372	0.0278	0.0247
	(0.0132)***	(0.0126)**	(0.0135)*
Basic Internet			0.0007
			(0.0078)
PCs per employee			0.0152
			(0.0108)
Home Internet use		0.0823	0.0822
		(0.0379)**	(0.0379)**
Home Internet data missing		0.0281	0.0282
		(0.0170)*	(0.0170)*
Log population in 1990		−0.0065	−0.0068
		(0.0019)***	(0.0019)***
Percentage African Americans in 1990		0.0133	0.0124
		(0.0118)	(0.0119)
Percentage university graduates in 1990		0.5720	0.5590
		(0.0789)***	(0.0807)***
Percentage high school graduates in 1990		−0.1555	−0.1589
		(0.0520)***	(0.0522)***
Percentage below poverty line in 1990		−0.1615	−0.1598
		(0.0464)***	(0.0463)***
Median income in 1990 ($000)		−0.0006	−0.0006
		(0.0006)	(0.0006)
Percentage population attending Carnegie Type 1 schools in 1990		0.0320	0.0338
		(0.0475)	(0.0480)
Percentage population enrolled in engineering program in 1990		-0.2202	-0.2357
		(0.3630)	(0.3647)
Patents granted to inventors in the county in the 1980s (000)		0.0165	0.0160
		(0.0043)***	(0.0043)***
Percentage professional in 1995		−0.0102	−0.0089
		(0.0535)	(0.0543)
Percentage of persons over age 65 in 1990		0.0443	0.0470
		(0.0513)	(0.0513)
Net migration into the county in 1995 (000)		0.0033	0.0034
		(0.0032)	(0.0032)
Change in log total population between 1990 and 2000		0.0527	0.0539
		(0.0152)***	(0.0153)***
Change in percentage of African American 1990 to 2000		0.0265	0.0251
		(0.0756)	(0.0759)
Change in percentage of university graduates 1990 to 2000		0.8219	0.8161
		(0.1604)***	(0.1613)***
Change in percentage of high school graduates 1990 to 2000		−0.0224	−0.0259
		(0.0947)	(0.0947)
Change in percentage of persons over age 65 1990 to 2000		−0.5628	−0.5621
		(0.1192)***	(0.1190)***
Change in net migration into the county 1990 to 2000 (000)		0.0020	0.0022
		(0.0037)	(0.0037)
Constant	0.1848	0.2995	0.3006
	(0.0017)***	(0.0458)***	(0.0460)***
Observations	2,743	2,743	2,743
R^2	0.004	0.131	0.13

Notes: Dependent variable is change in logged wages from 1995 to 2000. Heteroskedasticity-robust standard errors in parentheses.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

TABLE 3—RELATIONSHIP PRIMARILY OCCURS IN PLACES THAT ARE ALREADY HIGH INCOME, EDUCATION, IT INTENSITY, AND POPULATION

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Advanced Internet	0.0168 (0.0137)	0.0120 (0.0125)	0.0246 (0.0127)*	0.0214 (0.0159)	0.0049 (0.0149)	0.0239 (0.0128)*	0.0067 (0.0150)
Advanced Internet and high income county	0.0960 (0.0389)**				0.0442 (0.0492)		0.0377 (0.0496)
Advanced Internet and high education county		0.1101 (0.0455)**			0.0770 (0.0548)		0.0757 (0.0547)
Advanced Internet and high population county			0.3631 (0.0934)***		0.2378 (0.1018)**		0.0182 (0.1027)
Advanced Internet and high IT-intensity county				0.0206 (0.0228)	0.0134 (0.0235)		0.0102 (0.0237)
Advanced Internet and high income, education, IT-intensity, and population county						0.4588 (0.1585)***	0.3393 (0.1904)*
Observations	2,743	2,743	2,743	2,743	2,743	2,743	2,743
R^2	0.13	0.13	0.13	0.13	0.14	0.14	0.14

Notes: Dependent variable is change in logged wages from 1995 to 2000. In addition to the controls in Table 2, regressions include dummies for the main effects of the interactions where appropriate (high income, high education, high IT intensity, high population, and high all factors). Internet at home is not included because Internet home data missing is collinear with high population. Heteroskedasticity-robust standard errors in parentheses.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

B. *When Was Advanced Internet Investment Related to Local Wage Growth?*

In this section, we establish the payoff puzzle. We demonstrate that advanced Internet investment was strongly correlated with local wage increases in counties with high income, education, and population, and a large percentage of IT-intensive firms. However, we also show that advanced Internet investment was largely uncorrelated with wage increases elsewhere. In short, advanced Internet increased regional wage inequality over 1995–2000.

Building toward equation (2), our regression results in Table 3 explore this pattern in several steps. Column 1 shows that advanced Internet is significantly associated with wage growth in counties in the top quartile of median income as of 1990. In contrast, counties in other quartiles with high levels of advanced Internet did not experience especially rapid wage growth. Advanced Internet therefore contributes to regional wage divergence.

Columns 2 through 4 show how variation in local education levels, IT intensity, and population shapes advanced Internet's impact. Column 2 shows that advanced Internet is associated with wage growth only for high education counties. The similarity with column 1 is not surprising because 60 percent of the counties overlap. Column 3 shows that counties with over 150,000 people display a strong association between advanced Internet use and wage growth.

Column 4 examines counties in the top quartile in IT intensity. There is no statistically significant incremental gain from advanced Internet investment in high IT-intensity counties. Nonetheless, we include IT intensity for three reasons. First, IT intensity has been emphasized in much of the previous literature linking IT to average productivity.[14] Second, the coefficient is positive, and, when added to the coefficient on the main effect in the first row, it is significantly different from zero with 99 percent confidence. Third, we tried several specifications, and the coefficient was sometimes significantly positive and never negative.

Column 5 shows that when we include all four measures of pre-Internet county strength (income, education, population, and IT intensity), only population appears significant. This may not be surprising given that there is considerable overlap between the measures: Each measure contains roughly 680 counties (high population, which is not based on quartiles, contains 315), of which 163 are in the top group in all measures. Column 6 shows that in these 163 counties advanced Internet is strongly correlated with wage growth. Column 7 estimates the specification in equation (2) and shows that it is the combination of more than one factor that drives the relationship between advanced Internet and wage growth.[15]

What does this mean? Increases in advanced Internet investment are related to higher wage growth in the 163 counties that were already doing well than in the other 2,580 counties in the sample. These results suggest that advanced Internet is related to 22.7 percent (6.5 percentage points out of 28.6 on average) of the total wage growth in the 163 counties that were already doing well in 1990. For the other counties, advanced Internet explains just 1 percent (0.21 percentage points out of 20.5 on average) of overall wage growth.[16] Using back of the envelope calculations, this means that advanced Internet explains over half of the 8.1 percentage point difference in wage growth between the average for those 163 counties and the other 2,580 counties in the sample.[17] In short, while Internet investment is widespread, the payoffs are not.

We stress these results reflect a general experience found in a set of urban counties. The inordinate influence of canonical outliers did not produce it. For example, removing Santa Clara or San Francisco from the dataset does not change the qualitative results. In part, this should not be surprising; no single variable, not even advanced Internet investment, could possibly explain the anomalous experience in Santa Clara in this time period (i.e., over 80 percent wage growth in five years). Broadly, counties with high advanced Internet use and wage growth are often centers of IT production and use; counties with high advanced Internet use but low wage growth are often small cities where the labor markets are not very tight; counties with low advanced Internet and wage growth span a range of experiences but include many rural areas; and counties with high wage growth but low Internet use are relatively rare.[18]

[14] See, for example, Stiroh (2002) or Jorgenson, Ho, and Stiroh (2005).

[15] As shown in the online Appendix, the core results of Table 3 are robust to numerous alternative specifications.

[16] These calculations use the coefficient estimates in Table 3 column 6, the average Internet use for the 163 counties, and the average Internet use in all other counties.

[17] More precisely, for the approximately 40 counties out of the sample of 163 counties with low Internet investment, the investment contributes little to explaining the difference in wage growth. Similarly, for the approximately 80 counties with mean values or higher, the Internet explains as much as half or more of the differences in wage growth. Indeed, at the maximum 0.253 (Arapahoe, CO) the Internet can explain all the additional wage growth.

[18] Counties among the top 163 that have high advanced Internet use and wage growth (both at least one standard deviation above the mean) include San Mateo and Santa Clara, Calif. (both in the San Francisco-Oakland-San Jose MSA); Boulder and Arapahoe, Colo. (Denver-Boulder-Greeley MSA); Fairfax, Va. (Washington-Baltimore MSA); Travis, Texas (Austin-San Marcos MSA); and Washington, Ore. (Portland-Salem MSA). Those with high advanced Internet use (one standard deviation above mean) but relatively low wage growth (below mean) include

C. *Justifying a Causal Interpretation*

This section provides the results of a variety of additional tests we run to address omitted variable bias and simultaneity. We first discuss the results of a series of instrumental variables estimates. Two of our instruments are correlated with local costs of Internet investment. First, we instrument using variance in the costs of Internet deployment among establishments in multiestablishment firms in the county. We measure the total number of programmers in other establishments and other counties, but in the same firm. Forman, Goldfarb, and Greenstein (2008) show that establishments that are part of firms with many programmers in other locations adopt faster (even if there are few programmers at the focal establishment). They argue for a causal interpretation, partly because these programmers would have been hired for reasons other than Internet investment. In other words, programmers elsewhere in the firm make Internet investment at the focal establishment more likely. We use the average across establishments within a county as an instrument. In these regressions, we also include a control for the proportion of establishments in multi-establishment firms, because the variable is defined only for such firms.

Our second instrument is the number of local county connections to ARPANET—a wide area data communications network that was a predecessor of the Internet—which will capture local data communications infrastructure and expertise. Both variables are unlikely to be correlated with unobservables influencing local wage growth. Our programmers variable reflects the presence of IT skills in linked counties. And ARPANET reflects historical decisions (from the 1970s) about connectivity to Department of Defense or US university networks.

Our third and last instrument is an industry-level proxy of the demand for advanced Internet investment outside the focal county, which is sometimes called a Bartik index.[19] For each county, we compute the mean propensity to adopt Internet by industry. This is average industry adoption excluding the establishments in the focal county. We then sum these industry propensities up, using as weights the percentage of establishments in each industry in the local county.[20] To the extent that it reflects industry-level propensities to adopt advanced Internet and variance in industry composition across counties this variable should be correlated with adoption; however, it excludes local and establishment-specific features of the county and so should be uncorrelated with local wage growth. This instrument therefore links industry to wage growth and assumes advanced Internet as the mechanism.

Columns 1, 3, 5, and 7 of Table 4 present the results of LIML instrumental variable estimates of Table 2 column 2. We present the results of just-identified median-unbiased results in columns 1, 3, and 5, and a combination of these three instruments in column 7. The first-stage results suggest that advanced Internet investment is increasing in the number of linked programmers found elsewhere in county

Madison, Ala. (Huntsville, AL MSA), Lake, Ohio (Cleveland-Akron MSA), Kalamazoo, Mich. (Kalamazoo-Battle Creek MSA), and Middlesex, Conn. (New London-Norwich MSA). Only Hudson, N.J. (New York-Northern New Jersey-Long Island MSA) has high wage growth (one standard deviation above mean) but relatively low advanced Internet use (below mean).

[19] Our index shares similarities with indexes used by Bartik (1991) and Blanchard and Katz (1992).

[20] Formally, for each county i, and industry j, compute $\hat{\theta}_{ij}$, the average adoption rate for industry j excluding the establishments in county i. The instrument is equal to $\hat{\rho}_i = \sum_j \gamma_{ij} \hat{\theta}_{ij}$, where γ_{ij} is the share of establishments in industry j in county i.

Table 4—Instrumental Variables Analysis of Table 2 Column 2 and Table 3 Column 6

	Programmers in other establishments within the same firm		Bartik index		ARPANET nodes		All three instruments	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FIRST STAGE: Dependent variable is advanced Internet								
Programmers in other establishments within the same firm	0.00017 (0.00005)***	0.00016 (0.00004)***					0.0002 (0.00005)***	0.0002*** (0.00005)
Bartik index			0.2990 (0.1774)*	0.2681 (0.1809)			0.2612 (0.1790)	0.2359 (0.1822)
ARPANET nodes					0.0058 (0.0048)	0.0116 (0.0172)	0.0052 (0.0046)	0.0078 (0.0174)
Programmers in other establishments within the same firm and high all factors		0.00004 (0.0001)						0.00002 (0.0001)
Bartik index and high all factors				0.4084 (0.7077)				0.2359 (0.1823)
ARPANET nodes and high all factors						−0.0077 (0.0174)		−0.0042 (0.0176)
Partial R^2	0.0067	0.0063	0.0022	0.0017	0.0001	0.0001	0.0084	0.0078
F-statistic	12.41	6.87	2.84	1.67	1.47	0.76	5.77	3.11
FIRST STAGE: Dependent variable is advanced Internet and high all factors								
Programmers in other establishments within the same firm		−4.86e-07 (4.45e-07)						−3.58e-07 (4.38e-07)
Bartik index				0.0009 (0.0015)				0.0011 (0.0014)
ARPANET nodes						−0.0011 (0.0008)		−0.0002 (0.0007)
Programmers in other establishments within the same firm and high all factors		0.00023 (0.00011)**						0.00018 (0.00011)
Bartik index and high all factors				1.3382 (0.5054)***				0.8730 (0.5214)*
ARPANET nodes and high all factors						0.0072 (0.0032)**		0.0049 (0.0029)*
Partial R^2		0.0613		0.0443		0.0098		0.0898
F-statistic		3.33		3.62		2.82		3.20
SECOND STAGE: Dependent variable is logged wages								
Advanced Internet	0.2781 (0.1490)*	0.2252 (0.1494)	0.0156 (0.2374)	−0.1218 (0.2892)	2.4859 (2.1301)	−0.0724 (0.7287)	0.2752 (0.1587)*	0.1791 (0.1654)
Advanced Internet and high income, education, IT-intensity, and population county		0.7456 (0.5835)		1.9206 (0.8584)**		3.0077 (1.2898)**		1.3741 (0.5992)**
Overidentification test (p-value)	N/A	N/A	N/A	N/A	N/A	N/A	0.158	0.388
Hausman test (p-value)	1.000	1.000	1.000	1.000	1.000	0.942	1.000	1.000
R^2	0.13	0.03	0.13	0.06	0.13	0.04	0.13	0.06

Notes: Dependent variable is change in logged wages from 1995 to 2000. In columns 1, 3, 5, and 7, controls are the same as Table 2. In columns 2, 4, 6, and 8 controls are the same as Table 3. Heteroskedasticity-robust standard errors in parentheses. Observations is 2,743.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

establishments, in industry propensity to adopt advanced Internet, and (weakly) in the number of historical ARPANET nodes. The *F*-statistic for the first stage instruments ranges from 12.41 for our just-identified estimates using programmers, to a weaker 1.47 for our just-identified estimates using the ARPANET instrument. The results of these regressions remain qualitatively similar to our main specification in Table 2 column 2, though we obtain significance only when including the programmers instrument. The coefficient on advanced Internet rises, perhaps because the programmers and ARPANET instruments apply most to the places that were already doing well, particularly in terms of IT-using firms. In other words, while the instrument is appropriate in the sense that it is uncorrelated with wage growth except through advanced Internet, the treated group is disproportionately the set of counties that had the most potential to be affected by the Internet. Despite the coefficient increase, a Hausman test retains the null that the coefficients in Table 4 and column 2 of Table 2 are the same with *p*-values of 1.000 in all cases; however, this is largely because the coefficients on the controls change little. For the overidentified regression, the *p*-value of the overidentification test statistic is 0.158. While the results are somewhat noisy, these IV estimates do suggest a statistically significant but economically weak link between advanced Internet investment and wage growth.

Next, we turn to instrumental variables analysis of our core result that the Internet is most strongly associated with an increase in wages in a handful of counties. Table 4 columns 2, 4, 6, and 8 present the results of regressions that instrument for advanced Internet and its interaction with *HighAllFactors*. We interact each of our original instruments with an indicator for being located in one of the *HighAllFactors* counties. The resulting instruments are combined with the original set to form a total of six instruments for two potentially endogenous variables. The *F*-statistics for the first stage estimates are quite low. Therefore, despite the significance of the interactions in the first stage, the instruments for the *HighAllFactors* and advanced Internet interaction are still weak. Nevertheless, the finding that the results are generally significant when the instruments are used separately is encouraging.

The estimates support the results of Table 3 column 6 that the marginal effect of advanced Internet on local wages is stronger in *HighAllFactors* counties than in other counties. Moreover, with the exception of column 2, advanced Internet's interaction with *HighAllFactors* is positive and statistically significant, and of similar magnitude to the related estimate in Table 3 column 6. Again, although the Hausman tests retain the null that the coefficients in Table 4 and Table 3 column 6 are the same, this is largely because the coefficients on the controls change little. The main coefficient of interest is substantially higher in the instrument variables regressions than in the other regressions. As in Table 4, this increase is likely due to the instruments being strongest in the counties with the largest potential marginal benefit from advanced Internet.

Next, we examine a falsification test. We examine whether our measure of Internet investment contributes to regional wage divergence prior to 1995. As noted above, advanced Internet investment should contribute to wage growth only in the latter half of the 1990s.

Figure 2 provides a graphical representation of the results of this falsification test. It shows a replication of the results in Table 3 column 6 using a panel of all years

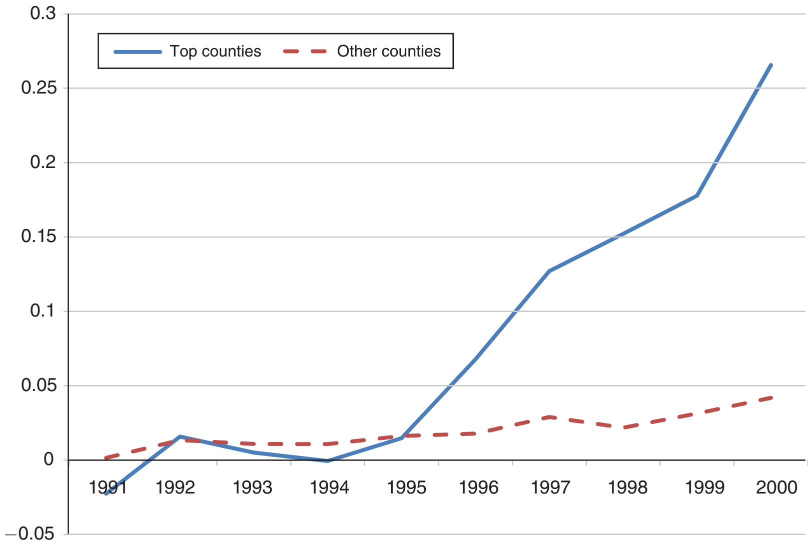

Figure 2. Marginal Effect of Advanced Internet Year-by-Year in Top Counties

Notes: This is based on a panel version of the regression model in Table 3 column 6 where each year from 1990 to 2000 is included in the regression and a separate effect of advanced Internet (as of 2000) and the interaction was estimated for each year. Controls are the same as in Table 3.

from 1990 to 2000. The controls are the same as in column 6, and the dependent variable is logged wages. We interact year dummies from 1991 to 2000 with the measure of advanced Internet (as of 2000) and the interaction of advanced Internet with *HighAllFactors*. This generates a measure of the association between advanced Internet (measured as of 2000) and wages across county types over the period. We expect no relationship between the advanced Internet measure and the wage difference between *HighAllFactors* counties and other counties prior to the actual diffusion of the Internet. Figure 2 clearly shows this pattern: advanced Internet is not correlated with a wage difference until 1996 (when the internet began to diffuse widely). Between 1991 and 1995 the coefficients on both variables are statistically indistinguishable from zero in every year. Starting in 1996, we begin to see a difference associated with advanced Internet investment. In these latter years, the association between advanced Internet and local wage growth in well-off counties is larger than that in other counties, and this difference is statistically significant. Further, all of the coefficients for the interaction between advanced Internet and *HighAllFactors* counties over 1996–2000 are greater than the coefficients for the same interaction over 1991–1994 (and these differences are also statistically significant).

D. *Additional Implications*

In this section, we discuss two additional results that inform our understanding of the consequences of the diffusion of advanced Internet on local economies. Table 5 columns 1 and 2 show the relationship between advanced Internet and employment. Advanced Internet is associated with an increase in employment in places that were

Table 5—Additional Implications of Advanced Internet Investment

Dependent variable→	Logged employment growth 1995 to 2000		Logged wage growth 1999 to 2005	
	Overall effect (1)	Interaction with places that were high in all factors (2)	Overall effect (3)	Interaction with places that were high in all factors (4)
Advanced Internet	−0.0190	−0.0206	−0.0057	−0.0053
	(0.0164)	(0.0166)	(0.0132)	(0.0134)
Advanced Internet and high income, education, IT-intensity, population county		0.2025		0.0007
		(0.1096)*		(0.1023)
Observations	2,743	2,743	2,743	2,743
R^2	0.32	0.32	0.06	0.06

Notes: In columns 1 and 3 controls are the same as Table 2. In columns 2 and 4 controls are the same as Table 3. Heteroskedasticity-robust standard errors in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

already doing well but is not associated with such an increase elsewhere. At average values of advanced Internet within *HighAllFactors* counties (13.5 percent), this suggests that *HighAllFactors* counties experienced employment growth 2.7 percentage points larger than all other counties as a result of investment in advanced Internet. Therefore, the employment results suggest the same puzzle as the wage results: despite investment in advanced Internet, many places did not receive benefits.

Table 5 columns 3 and 4 examine whether the lagging counties caught up after the dot-com crash. Specifically, they repeat the regressions in Table 2 column 2 and Table 3 column 6 but use wage growth between 1999 and 2005 as the dependent variable. The results suggest that counties maintained their new position in absolute terms. The leading counties did not grow faster, but their gains were not reversed either.

IV. Discussion

In this study, we find investment in advanced Internet is associated with significant wage and employment growth in locations with concentrated IT use, high income, high population, and high skills. We find little evidence of a payoff from Internet investment outside of these locations. A wide battery of specifications and exercises suggests these results represent causal relationships. In short, widely deployed Internet exacerbated regional income inequality.

These findings form a puzzle. They are consistent with three different classes of common models of how technology and human capital investments influence the wage distribution. First, skill-biased technical change could be partly responsible for the results, but it does not fully explain the regional distribution. Second, Marshallian (and other) externalities affiliated with agglomeration could shape the regional distribution, but it is puzzling why skilled labor is not sufficient everywhere.

Third, if changes in the productivity of certain industries alone were responsible, then measures of IT intensity alone should explain wage growth. Furthermore, none of these models explains why Internet investment was widely dispersed despite limited gains in many places.

Part of the puzzle arises due to data limitations. Data from this period are not detailed enough to allow examination of specific implications of distinct models. For example, are wage gains greatest for high, medium, or low-skilled occupations within a local labor market? How did wages change for managers and other coworkers for IT-intensive industries within a location?

The payoff puzzle also heightens questions about the long-run impact of advanced Internet investments. With time, labor mobility might alter the effect of further investments in advanced Internet on wage disparity; perhaps the regional wage divergence we document will disappear over time. While the results of Table 5 suggest no reversion by 2005, this is an incomplete assessment. A related open question concerns long-run gains to real wages. Nominal wage increases can become permanent changes in worker income or become a transfer to landowners through higher rents. Our evidence of short-run wage growth cannot make such a distinction.

Finally, our finding runs counter to the motivations for a wide array of policies encouraging Internet business use outside of urban areas. In contrast to the motivation frequently given for these subsidies, we find little economic impact from the Internet on wages in low density areas. Moreover, while our results suggest human capital plays a role in the payoff puzzle, the most common policies for subsidizing infrastructure focus on physical capital investments only.

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