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Post-pandemic Productivity Dynamics in the United States

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ABSTRACT: We study U.S. labor productivity growth and its drivers since the COVID-19 pandemic. Labor productivity experienced large swings since 2020, due to both compositional and within-industry effects, but has since returned to its pre-pandemic trend. Industry-level panel regressions show that measures of labor market churn are associated with higher productivity growth both in the cross-section and over time. Sectors with higher investment in digitalization, particularly in teleworkable industries, also experience higher productivity growth on average. There has also been an increase in business formation since the pandemic, but its impact on productivity dynamics will likely need more time to be reflected in the data.

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1 Introduction

Productivity is the main source of long-term improvement in living standards. In the current environment of elevated inflation and high debt, boosting productivity has become ever more important as a source for sustainable growth. Prior to the COVID pandemic, productivity growth in the US had been undergoing a secular slowdown since the mid-2000, coupled with a decline in broader business dynamism in terms of start-up rates, capital expenditure and labor mobility.

As the COVID-19 pandemic hit, there was a turbulent period of large productivity swings during the pandemic and re-opening driven by lockdowns of entire industries, followed by partial-reopening, renewed lockdowns and finally a full re-opening as vaccines paved the way for a return to normal life. Labor productivity exhibited large volatility throughout this period.

Leaving behind the pandemic and early re-opening phase, the US economy has shown encouraging rates of productivity growth since late 2022 that have lifted labor productivity to more than 6 percent above the pre-pandemic level by the first quarter of 2024. During this period, the US economy has also staged an impressive expansion against the background of rapid disinflation, suggesting that productivity growth and other supply-side tailwinds have likely been supporting strong growth in domestic demand. The surge in productivity also distinguishes the recovery in the US relative to other advanced economies, most notably the euro area, where flagging productivity has often been identified as a drag on growth potential (Schnabel, 2024).

In this paper, we zoom in on the productivity dynamics since the pandemic and examine the most salient drivers of the recent productivity rebound. We start by documenting the sectoral composition of productivity during the pandemic and re-opening versus productivity dynamics within sectors. We then move on to examine the role of some major trends that have been characteristic of the post-pandemic economy in driving productivity dynamics: telework, digital investment, labor market churn and new business creation.

Our main results are the following: productivity started to rebound in late 2022 primarily due to higher productivity growth within sectors, notably high-skill and IT-intensive sectors that had been experiencing faster productivity growth already prior to the pandemic (Information and Communication, Professional Services, Retail Services). These are sectors that had experienced a surge in digital investment already before the pandemic, and which saw another boost in digitalization from the shift to telework during the pandemic. The surge in reallocation of workers across jobs within and across industries, a crucial characteristic of the post-pandemic labor market, has further boosted productivity growth in sectors with the most labor churn. Taken together, investment in digitalization, particularly in teleworkable industries, and the increased dynamism among workers switching jobs, have all contributed to boosting labor productivity and drive the recent US recovery. It remains to be seen how long-lasting this trend will turn out to be. Finally, the increased rate in business formation we have observed since the pandemic and the emergence of AI could be additional productivity-boosting forces going forward, even though it is too early to detect their impact on productivity right now.

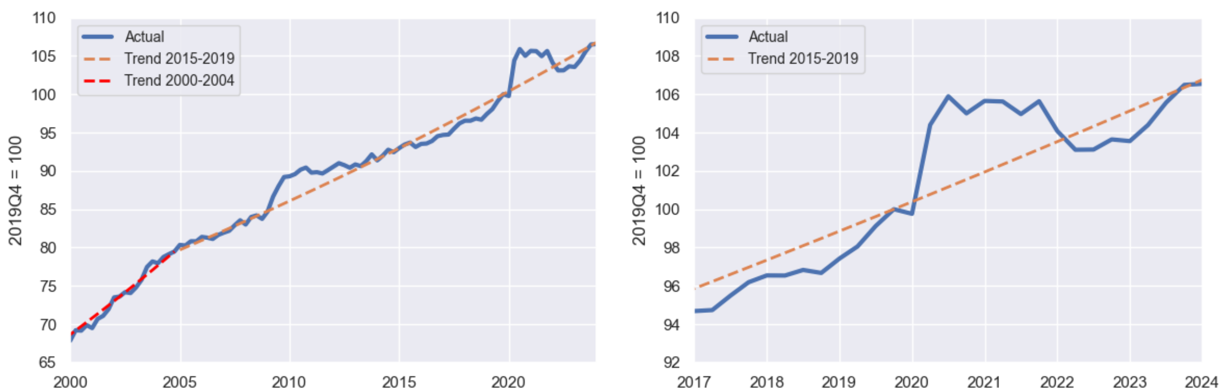
The rest of the paper is organized as follows. Section 2 presents some stylized facts on productivity and its drivers in the cross section and time series. Section 3 analyzes the empirical relationship between productivity and drivers more formally. Section 4 concludes.

2 Stylized facts

2.1 Aggregate productivity

Figure 1: Productivity v trend

(a) since 2000 (b) since 2017



Notes: Productivity indexed to 100 in 2019Q4. The trend in panel (a) from 2000 to 2004 (red) is calculated as the average productivity growth rate from 1995Q4 to 2004Q4, with the level set equal to (indexed) productivity in 2004Q4. The trend in panel (a) ranging from 2005 to 2023 (orange) and the trend in panel (b) are calculated as the average productivity growth rate from 2015Q1 to 2019Q4, and the level is indexed to 100 in 2019Q4. The latest observation is 2024Q1. Data is for non-farm business sector. Source: BLS.

Figure 1 shows labor productivity for the non-farm business sector since 2000.[1] The figure displays two noticeable patterns. The first is a slowdown of productivity growth since around 2005. Productivity growth from 2005 to 2019 was 1.5 percent, a relatively low level compared to the post-war (1950-2009) average of 2.2 percent.[2] The slowdown since 2005 followed a period of rapid average productivity growth of 3.2 percent from 1996 to 2004, often linked to the "dot-com" boom and its rapid advancement in information technology (Gordon and Sayed, 2022, Fernald and Li, 2022). The second pattern is the counter-cyclicality of productivity. Both after the Great Financial Crisis in

[1] Unless otherwise stated, whenever we refer to productivity we have in mind real output per hours worked, i.e. labor productivity.

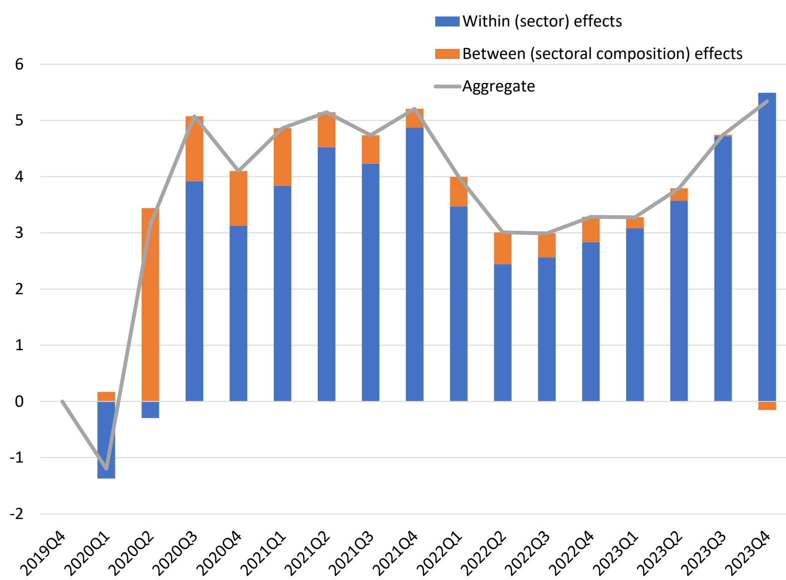
[2] These values are calculated as the average of the one-quarter annualized growth rates over the respective periods.

2009 and the pandemic recession in 2020, productivity increased markedly, but has subsequently returned to trend. This has been linked to “excess layoffs” by firms (Gordon and Sayed, 2022) during recessions as well as the cleansing effect of recessions (Caballero and Hammour, 1994, Kozeniauskas et al., 2022), where downturns induce low productivity firms to drop out of business and thereby raising average productivity.

In Figure 1 we plot productivity together with a piecewise-linear trend, calculated as the average productivity growth rate from 1995 to 2004, and 2005 to 2019, following Fernald and Li (2022). By the latest available observation, 2024Q1, productivity is 6.5 percent above its 2019Q4 level. This means productivity is right at its 2005 to 2019 trend. Average productivity growth since 2019Q4 was about 1.6 percent, close to the average from 2005Q1 to 2019Q4 (1.5 percent), and the average from 2015Q1 to 2019Q4 (1.6 percent).

2.2 Between-within decomposition

Figure 2: Between-within decomposition of productivity growth (percent, cumulative since 2019Q4)



Notes: Non-farm private sector. By 2-digit NAICS industry classification. Source: BEA, BLS.

Figure 2 decomposes the change in labor productivity relative to the end-2019 level into contributions coming from sectoral composition over time (between component) versus contribution from industry-specific productivity growth (within component).[3] As expected, the sudden lockdown in contact-intensive sectors in 2020Q2 led to a sharp increase in aggregate productivity due to a purely compositional shift, as lower productivity services sectors were shut down while higher-skilled higher-productivity sectors with less contact intensity largely continued operating. Over time though, the contribution of the between component waned, as services industries reopened, while the within-industry productivity change took hold. Within-industry productivity increased until late 2021, consistent with a cleansing effect of recessions. Productivity then declined in 2022 before growing consistently since late 2022 until the latest reading in 2023Q4. While the initial swings in within-industry productivity could be driven by measurement errors in hours worked (as workers and firms adopted telework), the increase starting in 2022Q3 appears to have gained momentum in 2023, ending the year at a level more than 5 percent higher than before the pandemic.[4]

Figure 11 in the appendix replicates the between-within analysis from 2007Q4 to 2019Q4. Over this time period, the between component played a more important role, dragging aggregate productivity down by 17 percent of the total productivity increase over this period.

2.3 Sectoral productivity patterns

Next, to see which sectors have been accounting for the within-sector dynamics, we plot in Figure 3 the growth in labor productivity over 2019Q4 to 2023Q4 and compare it to average growth over 2015Q1 to 2019Q4 prior to the pandemic. We observe that productivity growth since the pandemic has been most pronounced in high-skilled services, and low or even negative in more contact-intensive and lower-skilled service sectors. The sectors contributing most to cumulative productivity growth since the pandemic are Information and Professional Services, which combined together have contributed over 70 percent of overall productivity growth since end-2019 to end-2023.[5] The worsening productivity in construction sector is consistent with previous studies (Goolsbee and Syverson, 2023).

Interestingly, sectors that have seen faster productivity growth since the pandemic are also those that had been experiencing faster productivity growth prior to the pandemic. In other words, the sectoral pattern in productivity growth remained largely unchanged in spite of large shifts to the

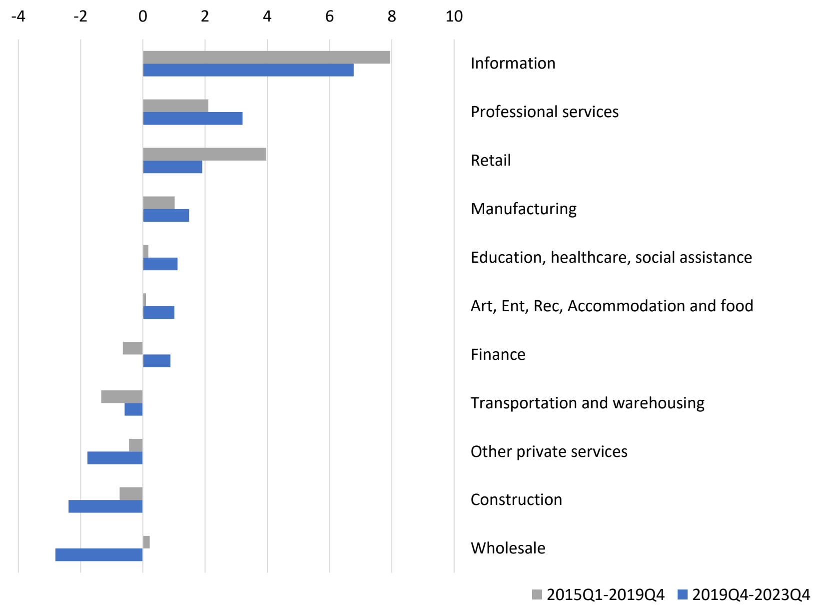
[3]The between-within decomposition is conducted based on 13 industries in the non-farm private sector, using the 2-digit NAICS industry classification. Appendix A.1 shows details on the decomposition.

[4]The difference in the cumulative growth number in this paragraph compared to Figure 1 is due to different data sources as well as economy aggregates used to calculate labor productivity: Figure 1 is based on Bureau of Labor Statistics (BLS) data, and refers to the non-farm business sector, while Figure 2 uses data from both the Bureau of Economic Analysis (BEA) and BLS. The economic aggregate of the latter is the non-farm private sector, i.e. including what the BEA classifies as the Households sector and Non-profit institutions serving households (NPISHs) sector. To the best of our knowledge, a sectoral decomposition, by economic activity, of output and hours worked, needed for the between-within analysis, is only available for the private sector.

[5]Figure 12 in Appendix A.1 decomposes aggregate productivity growth into contributions by sectors.

sectoral composition and other structural changes that have impacted product and labor markets. This cross-sectional stability suggests that the underlying drivers for productivity may not have shifted materially after relative to before the pandemic.

Figure 3: Average productivity growth by sector (within), 2019Q4-2023Q4 and 2015Q1-2019Q4 (percent, annualized)



Notes: Non-farm private sector. Sub-sectors "Mining" and "Utilities" not shown. Source: BEA, BLS.

2.4 Salient drivers

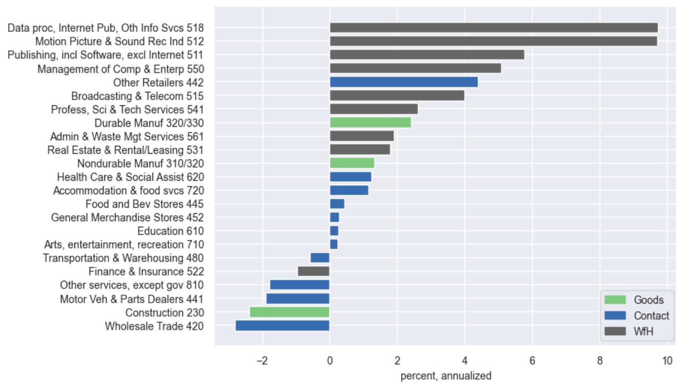
2.4.1 Telework

There is one structural change that has been profound to both workers and firms in the post-pandemic world, namely the shift to telework. Shift to telework and hybrid work is a megatrend of our times and is having deep implications for the future of work, housing markets, worker mobility, workplace amenities and wage bargaining dynamics. One key question is whether telework has led to higher productivity. While a thorough study of this question would require much more granular data and research design, we aim to check whether at the aggregate level, there are any discernible patterns in support of this hypothesis: Was productivity growth stronger in teleworkable industries?

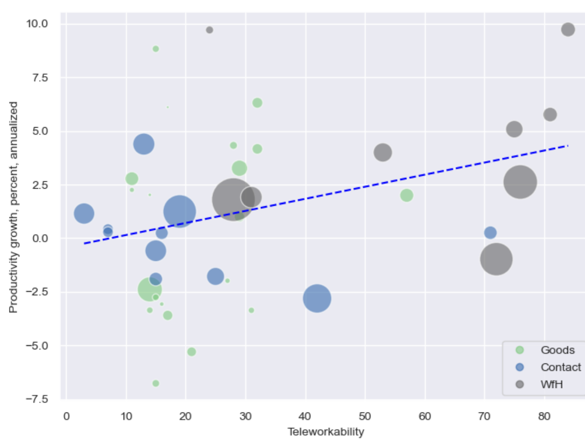
At first blush, we do observe in Figure 4 that among industries with the fastest productivity growth since the pandemic, a majority (8 out of the top 10) are those with predominantly teleworkable jobs (using the Gordon and Sayed (2022) teleworkability classification).

Figure 4: Productivity growth v telework

(a) Average productivity growth, by industry, 2019Q4 to 2023Q4



(b) Average productivity growth (2019Q4 to 2023Q4) v teleworkability



Notes: Top chart shows the average industry specific labor productivity growth from 2019Q4 -2023Q4, percent, annualized. Y-axis labels show industry name and NAICS code. Industries are grouped into manufacturing and construction ("Goods", green), contact-intense industries ("Contact", blue), and work-from-home industries ("WfH", gray), according to Gordon and Sayed (2022). Bottom chart shows the cross-sectional correlation between teleworkability (as measured by the Dingel and Neiman (2020) index) and productivity growth, measured over 2019Q4-2023Q4, percent, annualized. Blue dashed line is from (unweighted) regression of productivity growth on teleworkability. By NAICS 3 industry classification, with manufacturing industries aggregated. Source: BEA, BLS.

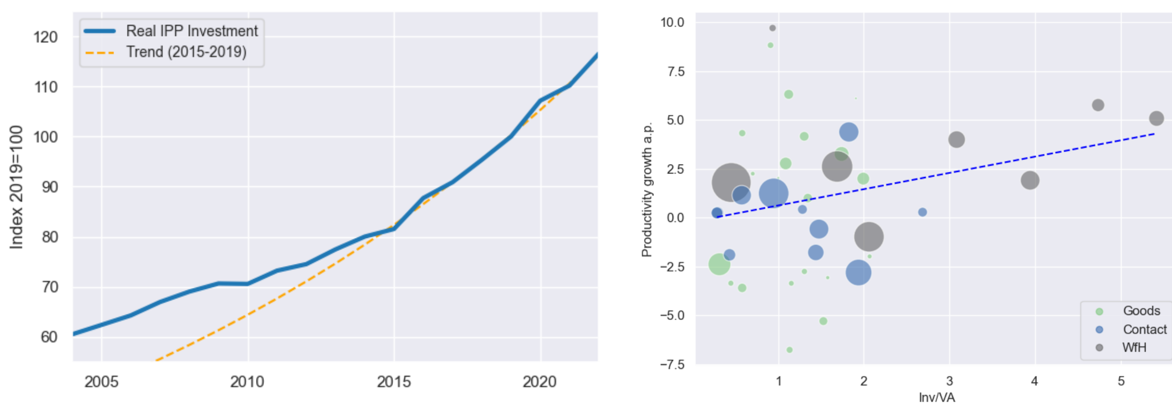
In the more formal analysis below, we will determine whether this correlation in the cross section of industries still holds if we control for other important forces for productivity growth.

2.4.2 Digitalization

Overall investment had been on a declining path in the US since the mid-2000, but there was a growing rate of investment in intellectual property products (IPP) since 2015 (see left chart in Figure 5). This relatively strong trend in investment in IPP (which includes investment in software, as well as spending on research and development), was even surpassed in 2020 and maintained throughout the pandemic and post-pandemic period. IPP investment facilitates the deepening of digitization of the workplace. And digitization is recognized to be an important driver for productivity growth particularly in modern services industries (Jaumotte et al., 2023).

Figure 5: Productivity growth v digitalization

(a) Real IPP Investment: Actual v Trend (b) Scatter



Notes: Panel (a): Real IPP investment is measured as percent of real value added. Orange line shows trend from 2015-2019. Aggregate of non-farm private sector. Panel (b): bubbles are proportional to industry-specific value added in 2019Q4. Vertical axis shows productivity growth, average from 2019Q4 to 2023Q4. Horizontal axis shows real investment rate, average from 2015 to 2019. Industries are grouped into Manufacturing and Construction (Goods, green), contact-intense industries (Contact, blue), and work-from-home industries (WfH, gray), according to Gordon and Sayed (2022). Industry Data Processing, Hosting, and Related Services (518) excluded due to its outlier position. Sectors “Mining” and “Utilities” excluded from both panels. Source: BEA, BLS.

2.4.3 Labor market churn

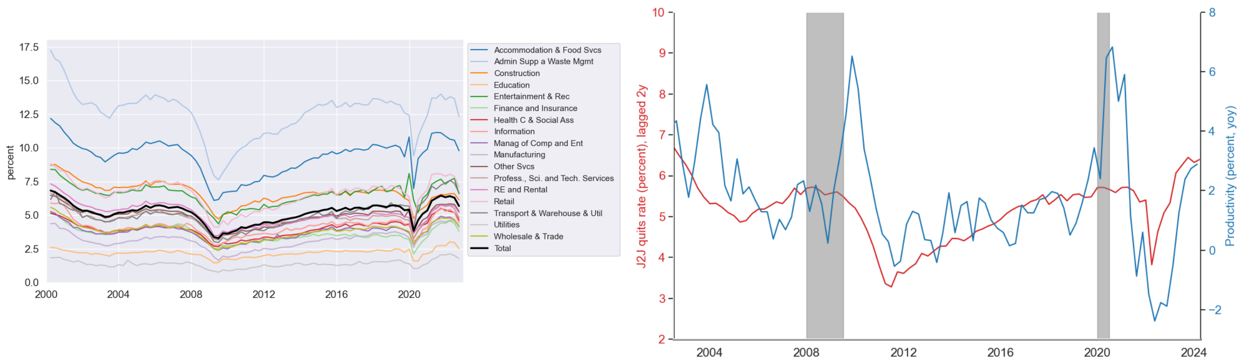
The pandemic and post-pandemic years have witnessed an increased rate of churn in the labor market. Quit rates soared, vacancy rates (as a share of employment or ratio to the number of unemployed) had reached record levels, as have other measures of dynamism (hiring, business application, firm births). Historically, higher rates of churn have been associated with higher productivity growth, as employer-employee matches are upgraded and job switchers tend to achieve higher wages. In addition, a higher quit and hiring rate is also by itself a force for stronger capital investment as firms seek to boost the marginal product of labor in the face of higher labor cost (Barnichon, 2014).

We document a broad-based increase in job-to-job quits across all industries in Figure 6, and how the time-series variation in job-to-job churn has been correlated with productivity growth over time.

Figure 6: Productivity growth v labor market churn

(a) J2J quits by sector

(b) J2J quits (lagged) v productivity growth



Notes: Job-to-Job separations/quits rate in panel (b) is lagged by two years. Shaded areas denote NBER recessions. Source: Longitudinal Employer-Household Dynamics (Census Bureau), FRED.

2.4.4 New business formation

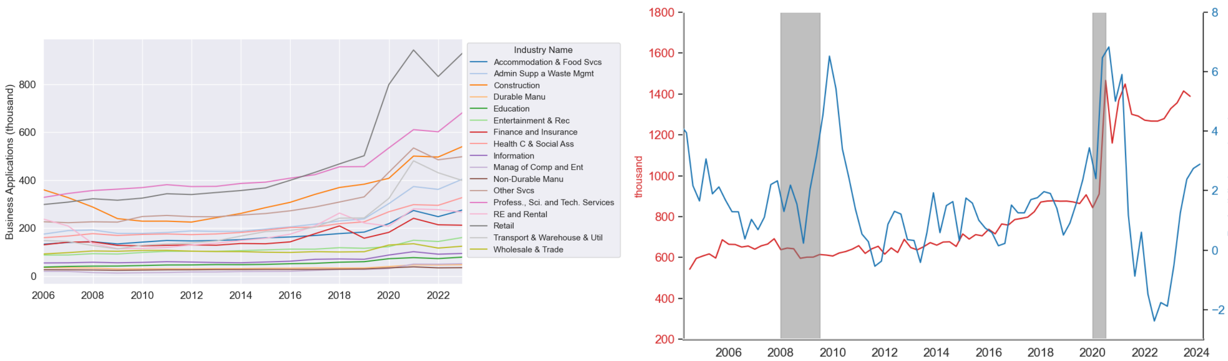
The churn in the labor market triggered by the pandemic and its aftermath also went hand in hand with a burst in new business applications and subsequent firm births. Decker and Haltiwanger (2023) and Decker and Haltiwanger (2024) document a sharp increase in start-up rates, concentrated in IT-intensive sectors, which has potentially led to rising innovation activity and productivity growth. We confirm the sharp increase in new business formation since late 2021 in Figure 7. While business application volumes rose to different extent across sectors, the aggregate shift does seem to correlate with overall productivity growth over time.

3 Empirical Analysis

Having established some salient stylized facts, we now turn to a more formal analysis of productivity drivers in the remainder of the paper. We first describe the various variables used in the subsequent regressions, their construction and data sources, as well as the framework for our empirical specifications to follow. Motivated by the stylized facts, we perform panel regressions of industry-level productivity growth on the main potential drivers: IP/ICT investment, labor churn (using various measures), teleworkability, and business formation. We exploit both the cross-sectional as well as the within-industry variation, depending on data availability.

Figure 7: Productivity growth v business applications

(a) Business applications by sector (b) Business applications v productivity



Notes: Panel (a) shows business applications by sector. Panel (b), red line, shows business applications, in thousands, left axis, blue line shows productivity growth, percent, yoy, right axis. Shaded areas denote NBER recessions. Source: Business Formation Statistics (Census Bureau), FRED.

3.1 Data and regression specifications

To create a dataset on real value added per hour, we combine quarterly data on GDP by industry from the Bureau of Economic Analysis (BEA) with Bureau of Labor Statistics (BLS) industry data on hours worked (U.S. Bureau of Economic Analysis, 2024*b*, Bureau of Labor Statistics, 2024*a*). Digitalization measures are based on the BEA's Detailed Data for Fixed Assets and Consumer Durable Goods (U.S. Bureau of Economic Analysis, 2024*a*). We construct real investment rates for software capital, information and communication technology (ICT) capital, and intellectual property products (IPP) capital, as alternative measures of investment in workplace digitization.[6] This dataset is only available at annual frequency, with the latest available data in 2022. Measures of labor market churn are from the Job Openings and Labor Turnover Survey (JOLTS) from the BLS (vacancy rate, quits rate; Bureau of Labor Statistics (2024*b*)). In addition, we use job-to-job flows (job-to-job separation/quits rate) from the Census Bureau's Longitudinal Employer-Household Dynamics program (Census Bureau, 2024*b*). We use data on business applications from the Census Bureaus's Business Formation Statistics (Census Bureau, 2024*a*). For our main analysis, we aggregate the data to have a uniform sector classification consisting of fourteen sectors roughly at NAICS 2 industry classification level. Throughout the analysis, we drop the Agriculture, Mining, and Public Administration sector from the analysis. Finally, as a measure of teleworkability we use the Dingel and Neiman (2020) teleworkability index. This index assigns a value ranging from 0 (not teleworkable) to 100 (fully teleworkable) to industries, but is time-invariant. We aggregate to our sector level using real output in 2019 as weights.

[6] We use the ICT measure constructed in Eden and Gaggl (2018) that combines hardware, software and communication equipment and R&D activities for these categories. While software capital is fully included in both ICT and IPP capital, ICT and IPP investment each cover different subcategories of capital goods from the BEA's Detailed Data for Fixed Assets and Consumer Durable Goods dataset.

To examine more formally the relationship between productivity growth and its salient drivers, we estimate panel regressions of the following form:

$$Y_{it} = \alpha_i + \tau_t + X'_{i,t-k}\beta + \epsilon_{i,t}$$

where $Y_{i,t}$ is the dependent variable of interest of industry i in year t (productivity growth or investment rate), $X_{i,t}$ is a vector of explanatory variables of interest (teleworkability, investment rate, labor market churn, firm churn), k denotes the lag structure of explanatory variables, α_i denotes industry fixed effects and τ_t denotes time fixed effects. The vector β contains coefficient estimates of interest. Since some variables are only available at annual frequency, we conduct the regression analysis at annual frequency.

3.2 Results

IPP Investment and Churn

We first look at a multivariate regression with several candidate drivers of productivity growth motivated by the previous section. We have three measures of labor churn: the vacancy rate, quits rate, and job-to-job quits rate, and show specification that contain each one of the measures in isolation. Our firm churn variable is the number of business applications, which we measure relative to sector real value added to account for differences in sector size.[7] We also add the real investment rate in IPP capital. We expect the explanatory variables to have a delayed impact on productivity growth, which is also suggested by time series patterns from the previous section. Therefore, we add the explanatory variables with a lag of two years. The sample runs from 2011 to 2023. Table 1 shows the results for both pooled and panel regressions. Table 3 in the appendix shows the corresponding results with ICT investment.

[7] This approach is similar in spirit to Decker and Haltiwanger (2023), who set business formation relative to population size in their geographical analysis of firm churn. See, for example, their section 4.3.

Table 1: Panel: Labor Churn, firm churn, and investment (IPP), 2011-2023

VARIABLES	(1) g_A	(2) g_A	(3) g_A	(4) g_A	(5) g_A	(6) g_A	(7) g_A	(8) g_A	(9) g_A	(10) g_A	(11) g_A	(12) g_A
Vacancy Rate	0.533***	0.962***	0.516***	0.677								
	(0.166)	(0.263)	(0.141)	(0.463)								
Quits Rate					0.968**	0.817**	1.510**	0.929				
					(0.431)	(0.399)	(0.603)	(1.024)				
J2J Quits Rate									0.410***	0.326**	1.132***	1.514*
									(0.152)	(0.138)	(0.349)	(0.740)
Firm Apps/VA	-0.002	0.002	-0.032	0.006	-0.009	-0.002	-0.022	0.017	-0.008	-0.002	-0.014	0.011
	(0.011)	(0.011)	(0.031)	(0.038)	(0.011)	(0.012)	(0.033)	(0.043)	(0.011)	(0.012)	(0.031)	(0.040)
IPP/VA	0.233***	0.246***	0.094	0.236	0.262***	0.266***	0.054	0.140	0.259***	0.261***	-0.171	0.161
	(0.040)	(0.040)	(0.670)	(0.701)	(0.040)	(0.041)	(0.703)	(0.753)	(0.039)	(0.040)	(0.709)	(0.773)
Constant	-2.280***	-2.785***	-0.771	-2.386	-2.176***	-2.200***	-2.012	-2.482	-2.319***	-2.226***	-3.977**	-6.530*
	(0.619)	(0.746)	(1.797)	(2.350)	(0.724)	(0.736)	(1.723)	(2.487)	(0.669)	(0.695)	(1.830)	(3.615)
Observations	182	182	182	182	182	182	182	182	182	182	182	182
R-squared	0.197	0.248	0.036	0.306	0.199	0.219	0.041	0.190	0.194	0.214	0.067	0.078
Industry FE	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Year FE	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is productivity growth (g_A). Explanatory variables: vacancy rate, quits rate (Source: JOLTS), job-to-job separation rate (J2J Quits Rate; Source: Census), real investment in IPP as share of real value added (IPP/VA), business applications relative to real value added (Firm Apps/VA); all lagged by two year. By NAICS2 industry classification. Annual sample, 2011 to 2023.

We find that the IPP investment rate and labor churn are the drivers that are most consistently related to productivity growth. In the pooled regression (columns 1, 5, and 9), investment rates and measures of labor churn are generally significant at at least the five percent level. A similar finding holds for a repeated cross-section, i.e a panel regressions where we include time fixed effects (columns 2, 6, and 10). Industries with more pronounced labor churn experienced faster productivity growth, conditional on IPP investment rates, and vice versa.[8] In a specification where we add non-IPP investment as regressor, the coefficient estimates generally remain stable, and the coefficient on non-IPP investment is insignificant. This result suggests that it is investment in IPP, that is, in digital capital and innovation, that matters for productivity growth, rather than other types of capital expenditure (Table 4 and Table 5 in the appendix).

For specifications with industry fixed effects alone (columns 3, 7, and 11), only labor churn variables are significantly related to productivity growth. This confirms more formally the time series co-movement suggested in Figure 6, Panel 2. Adding both industry and time fixed effects generally doesn't lead to significant results, except for job-to-job quits rates.

The implied magnitudes for the impact of labor churn on productivity growth are economically significant. For example, conditional on other variables staying constant, a one percentage point increase in the job-to-job quits rate is associated with a 1.1 percentage point increase in productivity growth, based on estimates using time series variation (column 11). The (unweighted) sector average

[8] Table 8 in the appendix analyzes the relationship between IPP investment and labor churn more formally.

job-to-job quits rate was 5.5 percent in 2019, and increased to 6 percent in 2022. The associated increase in the fitted value of productivity growth is 0.55 percentage points. Similarly, an industry with an increase in the real IPP investment rate by 1 percentage point is associated with an about 0.25 percentage point higher productivity growth rate. The mean IPP investment rate over sectors is about 4 percent in our sample, with a standard deviation of 5.8 percent. A one standard deviation increase in the IPP investment rate would therefore be associated with a 1.45 increase in productivity growth. In section 4 we will return to the question how much the variation in explanatory variables can explain productivity growth since the COVID-19 pandemic.

We do not find firm churn, as measured by business applications relative to real value added, to be significantly related to productivity growth in the panel. Appendix A.2 provides some cross-sectional evidence that increased firm churn since the COVID-19 pandemic could have had a positive impact on productivity growth. This is not surprising as prior to the pandemic, the rate of business creation was low and varied little across industries (see Figure 7 (a)), a trend well documented in the literature (see Decker and Haltiwanger (2023) and references therein). Therefore, using an industry panel from prior to the pandemic is unlikely to uncover any impact of business formation on productivity. The surge in business application and formation since late 2020 is a clear structural shift, and explains why firm churn has become a significant driver of productivity growth across sectors during the time since the pandemic.

Teleworkability, Investment and Churn

We repeat the multivariate regressions but include the Dingel-Neiman teleworkability index to the explanatory variables. The teleworkability index is time-invariant, so we can't include specifications with an industry fixed effect in this case. Otherwise, the approach and variables remain the same as before. Table 2 shows the results, and Table 6 in the appendix shows the corresponding results with ICT investment.

Table 2: Panel: Teleworkability, churn, and investment (IPP), 2011-2023

VARIABLES	(1) g_A	(2) g_A	(3) g_A	(4) g_A	(5) g_A
Telework	0.023**	0.024*	0.002	0.020*	0.017
	(0.012)	(0.012)	(0.010)	(0.011)	(0.011)
Telework x post-2019		-0.001	0.020	0.010	0.004
		(0.028)	(0.023)	(0.023)	(0.024)
Vacancy Rate			1.020***		
			(0.244)		
Quits Rate				1.093***	
				(0.392)	
J2J Quits Rate					0.399***
					(0.131)
Firm Apps/VA			0.005	0.002	0.002
			(0.012)	(0.012)	(0.012)
IPP/VA			0.239***	0.251***	0.247***
			(0.040)	(0.040)	(0.040)
Constant	-1.077*	-1.092*	-3.042***	-3.355***	-3.147***
	(0.637)	(0.655)	(0.837)	(0.923)	(0.859)
Observations	182	182	182	182	182
R-squared	0.049	0.043	0.245	0.227	0.216
Industry FE	N	N	N	N	N
Year FE	Y	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is productivity growth (g_A). Explanatory variables: Dingel-Neiman teleworkability index (Telework), vacancy rate, quits rate (Source: JOLTS), job-to-job separation rate (J2J Quits Rate; Source: Census), real investment in IPP as share of real value added (IPP/VA), business applications relative to real value added (Firm Apps/VA); all lagged by two year (except Telework). By NAICS2 industry classification. Annual sample, 2011 to 2023.

The Dingel-Neiman teleworkability index is positively related to productivity growth (column 1). The positive association hasn't changed since the start of the pandemic (column 2). The average teleworkability index in our sample is 30, the standard deviation is 23. The regression coefficient in column 1 implies that an increase in the index by one unit is associated with a 0.023 percentage point increase in the annual productivity growth rate. A one standard deviation increase in the teleworkability index is associated with an about 0.5 percentage point increase in the annual productivity growth rate.

However, once we account for real investment rates in IPP capital, as well as labor and firm churn (columns 3, 4, 5), the teleworkability index is only weakly associated with productivity growth. These results suggest that while teleworkable industries tend to have higher productivity growth, most of the variation is associated with other explanatory variables for productivity growth in the cross section. This results suggests that labor churn was particularly pronounced in industries that are amenable to telework and/or those with high rates of digital investment.[9] Furthermore, the pandemic didn't seem to change the association between teleworkability and productivity growth. Finally, coefficient estimates for the other explanatory variables remain significant, with magnitudes generally in line with results from Table 1.

4 Contributions to the change in productivity growth

How much of the time-series and cross-sectional variation can be accounted for by our candidate drivers of productivity growth? In this section we use our regression results from the previous section to address this question.

Fitted values – cross-sectional: To see how much *cross-sectional* variation can be explained by each driver, we calculate a fitted value $\Delta\hat{g}^X_{A,i}$ based on explanatory variable X for industry i according to:

$$\Delta\hat{g}^X_{A,i} \equiv \beta^X[\bar{X}_i - \bar{\bar{X}}] \tag{1}$$

where $\bar{X}_i$ is explanatory variable (labor churn, investment rate) for industry i, averaged over 2018-2021, and $\bar{\bar{X}} = \frac{1}{I}\sum \bar{X}_i$ is the average across the industries of the explanatory variable, averaged over 2018 to 2021 (explanatory variables enter the regression lagged by two years, which is why we average over 2018-2021), I denoting the number of industries. Here β^X is the coefficient estimate for explanatory variable X of columns 2, 6, and 10 in Table 1, respectively.

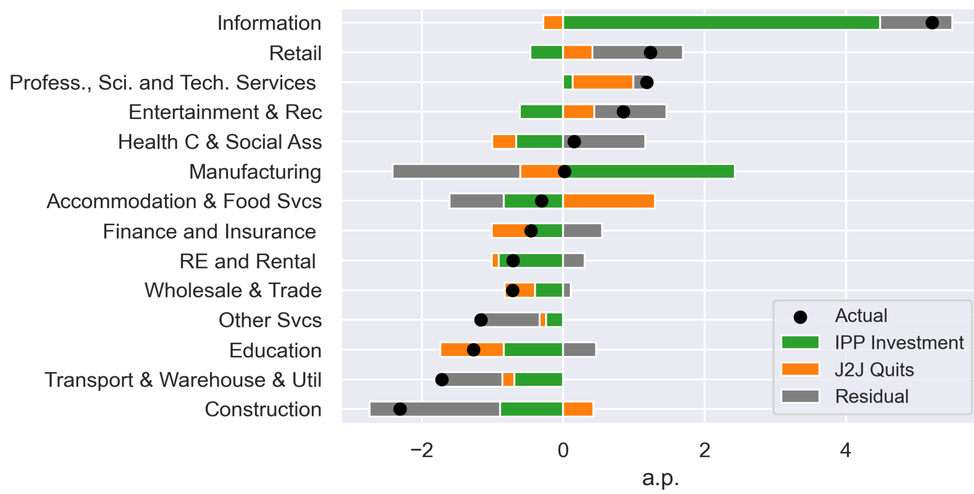
The fitted values are compared to respective realized industry growth rates, averaged from 2020 to 2023, in deviation from the average growth rate across industries over the same time period, i.e. $\bar{g}_{A,i} - \bar{\bar{g}}_A$, where $\bar{g}_{A,i}$ is the average productivity growth of industry i from 2020 to 2023, and $\bar{\bar{g}}_A = \frac{1}{I}\sum \bar{g}_{A,i}$ is the average productivity growth across industries from 2020 to 2023.

Figure 8 shows $\bar{g}_{A,i} - \bar{\bar{g}}_A$ and $\Delta\hat{g}^X_{A,i}$ for job-to-job quits and real investment rate in IPP by sector, while Table 13 and Table 14 in the appendix show the corresponding chart for the vacancy rate and quits rate, respectively. The strong productivity growth in the information sector, relative to the average growth rates across industries, is almost entirely accounted for by the higher rate

[9] Higher rates of reallocation in teleworkable industries could have contributed to higher productivity growth through better allocation of talent across firms, see Ji et al. (2024).

of IPP investment in the IT sector, while labor churn has a negative contribution to this sector. The job-to-job quits rate is, however, important to account for the stronger productivity growth in professional services, the entertainment and recreation sector, and the retail trade sector relative to the cross-sectional average. The cross-sectional regression model can account well for productivity growth in professional services, wholesale trade, and real estate and rental, but performs poorly for manufacturing and the construction sector, for which the residual is the largest.

Figure 8: Contributions to productivity growth from labor churn (job-to-job quits rate) and investment, cross-sectional variation



Notes: Black dot shows average productivity growth (Actual), green bar shows fitted value for real investment share in IPP capital (IPP Investment), the orange bar shows fitted value for job-to-job quits rate (J2J Quits), and gray bar is the residual. All values are averages from 2020 to 2023, in deviation from the industry average from 2020 to 2023. In annualized percent.

Fitted values – time series: Here we first calculate for each industry i the difference in growth rate ("time-delta") implied by the time-series variation in labor churn

$$\Delta \hat{g}^{churn}_{A,i,t} \equiv \beta^{churn}[churn_{i,t} - churn_{i,t-1}] \tag{2}$$

where $churn_{i,t}$ is labor churn variable of industry i in year t. For the calculations we use parameter estimates for β^{churn} in column 3, 7, and 11 in Table 1, respectively.

Second, we calculate the weighted average implied change in productivity growth rate, using share of real output as weights:

$$\Delta \hat{g}_{A,t} = \frac{1}{I}\sum_{i} \omega_{i,t} \Delta \hat{g}^{churn}_{A,i,t} \tag{3}$$

where $\omega_{it} = \frac{y_{i,t-1}}{\sum_i y_{i,t-1}}$, i.e. weights in year t are output shares of year $t-1$.

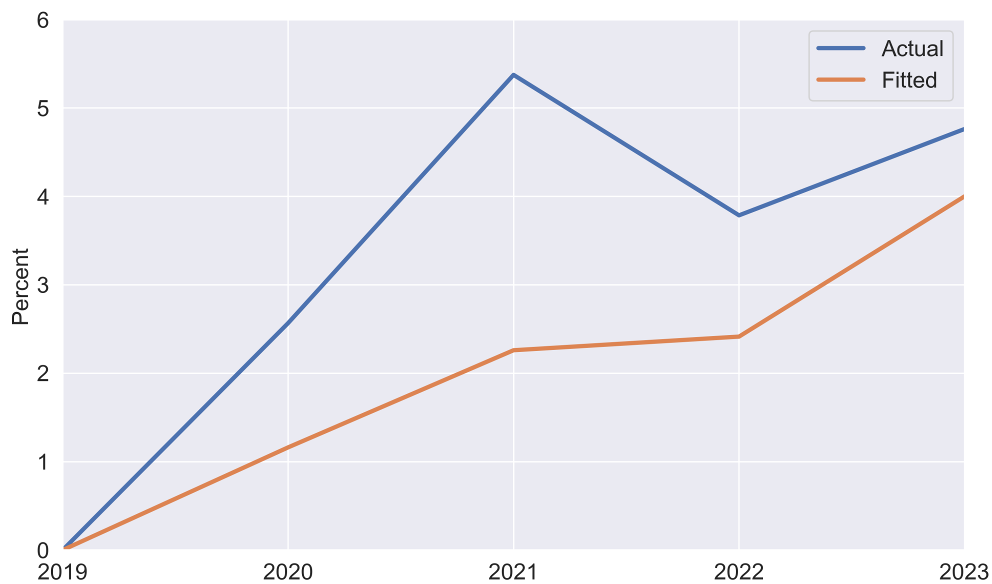
Third, we calculate implied productivity growth rates by combining an initial productivity growth rate and the respective "time-deltas" from the previous step:

$$\hat{g}_{A,2020} = g_{A,2019} + \Delta\hat{g}_{A,2020} \tag{4}$$

$$\hat{g}_{A,t} = \hat{g}_{A,t-1} + \Delta\hat{g}_{A,t} \tag{5}$$

Fourth, we take the cumulative sum of the implied productivity growth rates from step three to calculate the implied relative increase in productivity. We compare this series to the actual increase in within-sector productivity. The results using job-to-job quits are in Figure 9, and Figure 15 and Figure 16 in the appendix show results for quits and vacancy rate, respectively.

Figure 9: Contributions to weighted average productivity growth from labor churn (job-to-job quits rate), time variation



Notes: Figure shows for each year the increase in productivity in percent relative to 2019, both actual and fitted value using job-to-job quits rate. Actual and fitted value are aggregated by taking the weighted average of sectors, using real value added as weights.

The time series variation of the fitted value mirrors realized productivity, but with varying magnitudes. Unsurprisingly, the large increase in productivity in 2020 and 2021 is to a large extent not attributable to job-to-job quits. Other factors, like shifts in the sectoral composition, as highlighted in Figure 2, played a bigger role during the height of the pandemic and early re-opening. In addition, labor churn enters our specification with a lag of 2 years, so any sharp change in labor churn in 2020 would not yet be reflected in the fitted value. However, there is still a small positive contribution from labor churn to productivity growth during this period, owing to the relatively hot labor market and step up in churn we saw prior to the pandemic. The fall in productivity in 2022 is consistent with the fall in churn in 2020, and the upward slope of the fitted line falls considerably in 2022. The contribution from labor churn in 2023 is sizeable, consistent with the increase in job-to-job quits above the pre-pandemic level by 2021 shown in Figure 6.

Overall, the increased rate of job to job reallocation since 2020 can explain more than 80 percent of the cumulative increase in labor productivity from 2020 to 2023. Compared to measures of labor churn, the rate of IPP investment does not appear to explain as much variation in the time series as it does in the cross-section. Similarly, the burst in business formation, while more pronounced in industries with higher productivity growth on average, does not (yet) appear to drive recent productivity growth within industries.

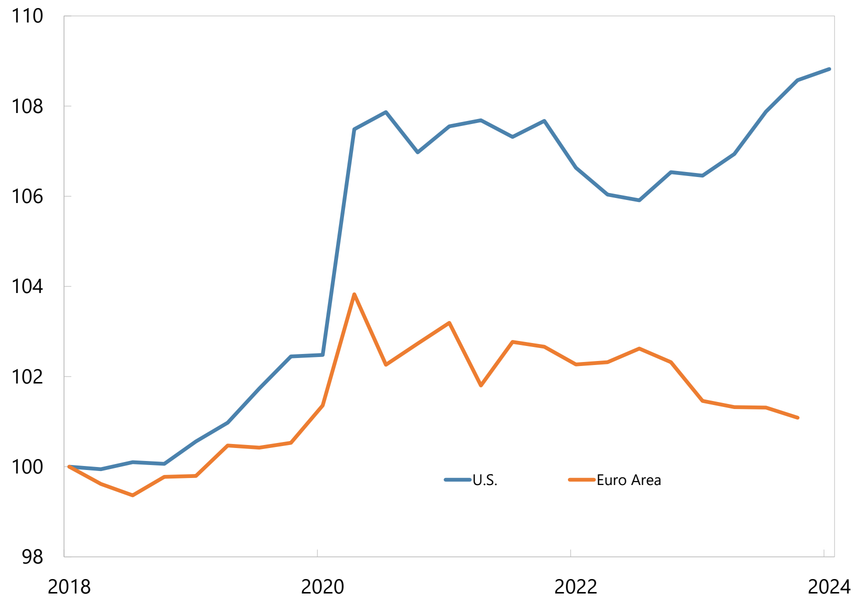
5 Conclusion

Rising productivity since end 2022 has provided considerable tailwind to US GDP growth during a period of high interest rates. In this paper, we have exploited the dynamics of productivity growth across industries since the COVID-19 pandemic and analyzed its determinants in the cross-section and over time.

Across industries, we see the recent rise in productivity being concentrated in the same set of industries which had also experienced relatively strong productivity growth before the pandemic. These are industries with higher rates of investment in IT capital and more amenable to telework since before the pandemic (most notably Information Technology and Professional Services). Both underlying trends, IP investment and transition to telework, accelerated further since the pandemic, thereby lifting productivity growth in these industries after an initial volatile period of adjustment to lockdown and re-opening. A new trend that further reinforced the productivity increase has been the sharply increased rate of worker churn across jobs. In particular, worker churn has had a more positive effect on productivity in a broader set of industries than IP investment, explaining therefore a large share of aggregate productivity increase in recent years. The increased rate of firm churn, manifested in a surge in business formation since the pandemic, has also been concentrated in industries with higher productivity growth, although their impact on productivity growth within industries is not yet notable in the relatively short time-series until now.

It is important to acknowledge that the strong growth in productivity since late 2022 through 2023 has so far been of a relatively short time span. Another observation important for contextualizing recent productivity performance is the fact that by the end of our sample, labor productivity (of the non-farm business sector) has merely returned to the pre-pandemic trend (Figure 1). The corollary

Figure 10: Labor Productivity for Total Economy: United States v Euro Area



Notes: Productivity indexed to 100 in 2018Q1. The latest observation is 2024Q1 for the United States and 2023Q4 for the Euro Area. Data is for total economy. Source: BEA, BLS, European Central Bank.

is that without the high rate of IP investment and labor reallocation, productivity would have drifted below trend in recent years. This is indeed what happened in a number of other advanced economies, most notably the euro area (see Figure 10), as well as in the US in the mid-2000. In other words, it appears that either a constant stream of technological innovation and/or capital deepening and enhanced factor allocation is necessary not only to boost, but even to maintain a certain productivity growth rate over time.

How long can the higher rate of productivity growth be sustained? On the one hand, investment in IPP may slow down, and rates of worker churn have already normalized to a great extent, both suggesting that the recent high rate of productivity growth may not continue for much longer. On the other hand, new technologies (AI) and continued high rates of new business formation may provide a new impulse for productivity growth, especially once interest rates come down and financial conditions for start-ups become more favorable.

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A Appendix

A.1 Additional Material for Section 2

Here we describe the between-within decomposition of Figures 2 and 11. We start with basic definitions:

$$A_t = \frac{Y_t}{h_t} \tag{6}$$

$$g_{A,t+h} = \frac{A_{t+h}}{A_t} - 1 \tag{7}$$

$$s_{it} = \frac{h_{it}}{\sum_i h_{it}} \tag{8}$$

$$Y_t = \sum_i Y_{it} \tag{9}$$

$$A_{it} = \frac{Y_{it}}{h_{it}} \tag{10}$$

Here, Y_t is real output in period t, h_t is hours worked in t, A_t denotes output per hours worked, i.e. labor productivity, in period t, $g_{A,t+h}$ denotes cumulative labor productivity growth from period t to $t+h$, s_{it} denotes the share of hours worked of sector i in t, Y_{it} is real output of sector i in t, and A_{it} is labor productivity in sector i in t.

We want to decompose the aggregate cumulative growth rate $g_{A,t+h}$ into a within-sector component g^W_{t+h} and a between-sector component g^B_{t+h}, such that $g_{A,t+h} = g^W_{t+h} + g^B_{t+h}$. The decomposition takes the following form:

$$A^B_{t+h} = \sum_i A_{it} s_{i,t+h} \tag{11}$$

$$\tilde{g}^B_{t+h} = \frac{A^B_{t+h}}{A_t} - 1 \tag{12}$$

$$A^W_{t+h} = \sum_i s_{it} A_{i,t+h} \tag{13}$$

$$\tilde{g}^W_{t+h} = \frac{A^W_{t+h}}{A_t} - 1 \tag{14}$$

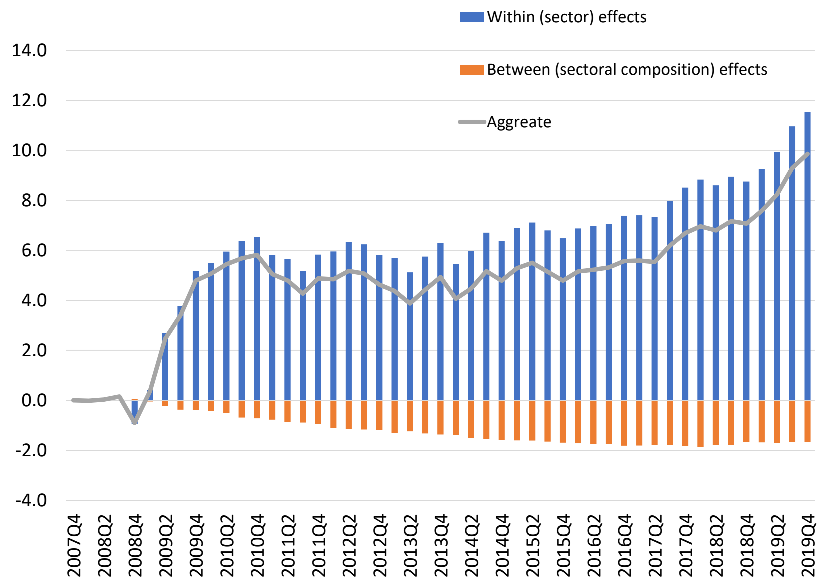
$$g^B_{t+h} = \tilde{g}^B_{t+h} \frac{1}{\tilde{g}^B_{t+h} + \tilde{g}^W_{t+h}} g_{A,t+h} \tag{15}$$

$$g^W_{t+h} = \tilde{g}^W_{t+h} \frac{1}{\tilde{g}^B_{t+h} + \tilde{g}^W_{t+h}} g_{A,t+h} \tag{16}$$

Here we rescale the within component $\tilde{g}^W_{t+h}$ and between component $\tilde{g}^B_{t+h}$ to get an exact decomposition of $g_{A,t+h}$.

Figure 11 shows the between-within decomposition for the pre-pandemic period, starting in the fourth quarter of 2007, the quarter before the previous recession started. Note that the between effect is now more substantially negative. What stands out over this period is that service sectors with below average productivity increased their hours-share considerably over this time period, contributing to a negative between component.

Figure 11: Between-within decomposition of productivity growth (percent, cumulative, 2007Q4 to 2019Q4)



Notes: Non-farm private sector. By 2-digit NAICS industry classification. Source: BEA, BLS.

To get a better understanding of which sectors drive aggregate productivity growth, we decompose aggregate (cumulative) productivity growth into contributions by sectors. This is interesting since even if a sector has a large within component, if it is a small sector it will not matter much for aggregate productivity growth. We define:

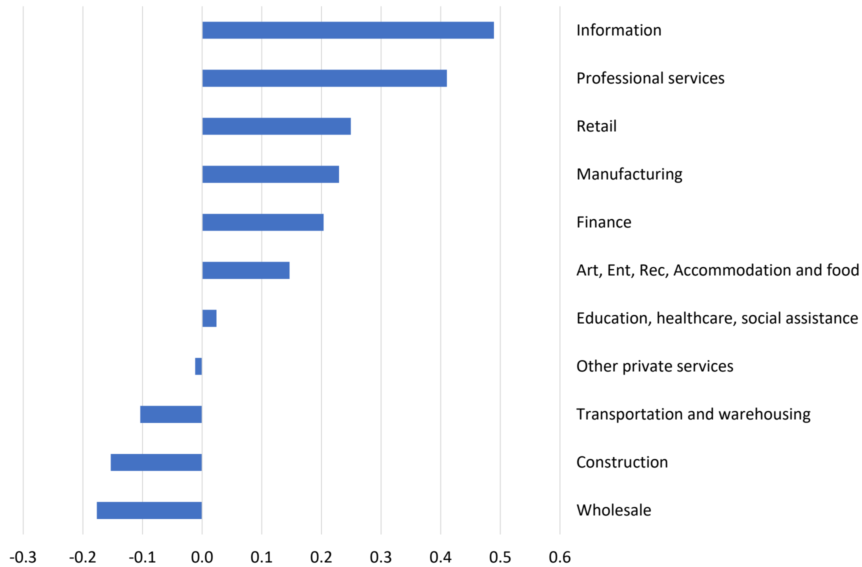
$$\tilde{g}_{A_i,t+h} = \frac{A_{it}}{A_t} \frac{s_{it}(A_{i,t+h} - A_{i,t}) + (A_{it} - \bar{A}_t)(s_{i,t+h} - s_{i,t})}{A_{it}} \tag{17}$$

$$g_{A_i,t+h} = \tilde{g}_{A_i,t+h} \frac{1}{\tilde{g}^B_{t+h} + \tilde{g}^W_{t+h}} g_{A,t+h} \tag{18}$$

$$\text{where } \bar{A}_t = \frac{1}{I} \sum_i A_{it} \tag{19}$$

Here $g_{A_i,t+h}$ is the contribution of sector i to cumulative productivity growth from t to $t+h$. We use a decomposition that combines both the within and between components of each sector, where between components only add positively if above average sectors are expanding or below average sectors are contracting, respectively. Here, $\bar{A}_t$ is average productivity across all sectors, and I is the number of sectors. Again, by rescaling we ensure that $g_{A,t+h} = \sum_i g_{A_i,t+h}$. Figure 12 shows the results.

Figure 12: Contribution of sectors to aggregate productivity growth, 2019Q4-2023Q4 (percentage points, annualized)



Notes: Non-farm private sector. Sub-sectors "Mining" and "Utilities" not shown. Source: BEA, BLS.

A.2 Additional Material for Section 3

Table 3: Panel: Labor churn, firm churn, and investment (ICT), 2011-2023

VARIABLES	(1) g_A	(2) g_A	(3) g_A	(4) g_A	(5) g_A	(6) g_A	(7) g_A	(8) g_A	(9) g_A	(10) g_A	(11) g_A	(12) g_A
Vacancy Rate	0.401**	0.693***	0.424***	0.824								
	(0.167)	(0.266)	(0.136)	(0.525)								
Quits Rate					0.902**	0.779**	1.275**	1.233				
					(0.425)	(0.391)	(0.539)	(1.072)				
J2J Quits Rate									0.380**	0.307**	0.948***	1.624*
									(0.150)	(0.137)	(0.288)	(0.753)
Firm Apps/VA	0.002	0.006	-0.032	0.006	-0.005	0.002	-0.026	0.017	-0.004	0.002	-0.023	0.011
	(0.011)	(0.011)	(0.023)	(0.033)	(0.012)	(0.012)	(0.026)	(0.037)	(0.011)	(0.012)	(0.022)	(0.035)
ICT/VA	0.289***	0.295***	0.372**	0.548**	0.322***	0.330***	0.377**	0.519**	0.320***	0.324***	0.262	0.523**
	(0.043)	(0.040)	(0.165)	(0.196)	(0.039)	(0.039)	(0.173)	(0.209)	(0.039)	(0.039)	(0.199)	(0.214)
Constant	-2.142***	-2.458***	-1.463*	-3.365*	-2.371***	-2.306***	-2.636***	-3.858*	-2.500***	-2.323***	-4.455***	-7.836**
	(0.579)	(0.696)	(0.746)	(1.597)	(0.697)	(0.688)	(0.822)	(1.980)	(0.647)	(0.646)	(1.294)	(3.239)
Observations	182	182	182	182	182	182	182	182	182	182	182	182
R-squared	0.226	0.270	0.047	0.309	0.242	0.267	0.053	0.313	0.238	0.262	0.072	0.206
Industry FE	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Year FE	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The dependent variable is productivity growth (g_A). Explanatory variables: vacancy rate, quits rate (Source: JOLTS), job-to-job separation rate (J2J Quits Rate; Source: Census), real investment in ICT as share of real value added (ICT/VA), business applications relative to real value added (Firm Apps/VA); all lagged by two year. By NAICS2 industry classification. Annual sample, 2011 to 2023.

Table 4: Panel: Labor churn, firm churn, and investment (IPP & non-IPP), 2011-2023

VARIABLES	(1) g_A	(2) g_A	(3) g_A	(4) g_A	(5) g_A	(6) g_A	(7) g_A	(8) g_A	(9) g_A	(10) g_A	(11) g_A	(12) g_A
Vacancy Rate	0.542***	0.980***	0.494***	0.702								
	(0.166)	(0.263)	(0.148)	(0.458)								
Quits Rate					0.984**	0.832**	1.483**	1.072				
					(0.432)	(0.400)	(0.588)	(1.021)				
J2J Quits Rate									0.413***	0.327**	1.080***	1.642**
									(0.151)	(0.138)	(0.358)	(0.740)
Firm Apps/VA	-0.003	0.001	-0.022	0.007	-0.009	-0.003	-0.013	0.019	-0.008	-0.002	-0.008	0.012
	(0.011)	(0.011)	(0.030)	(0.037)	(0.011)	(0.012)	(0.031)	(0.041)	(0.011)	(0.012)	(0.030)	(0.037)
IPP/VA	0.247***	0.267***	-0.175	0.084	0.277***	0.285***	-0.248	-0.025	0.271***	0.276***	-0.336	-0.049
	(0.044)	(0.044)	(0.630)	(0.667)	(0.043)	(0.045)	(0.671)	(0.730)	(0.042)	(0.045)	(0.668)	(0.737)
Non-IPP/VA	-0.034	-0.051	0.268	0.212	-0.035	-0.044	0.288	0.232	-0.027	-0.035	0.183	0.290
	(0.051)	(0.051)	(0.308)	(0.355)	(0.050)	(0.052)	(0.295)	(0.342)	(0.051)	(0.053)	(0.297)	(0.349)
Constant	-2.126***	-2.581***	-1.775	-3.200	-2.015**	-2.018**	-3.052	-3.534	-2.191***	-2.071***	-4.523**	-8.040*
	(0.703)	(0.792)	(2.175)	(3.146)	(0.789)	(0.782)	(1.958)	(3.290)	(0.765)	(0.761)	(1.968)	(4.380)
Observations	182	182	182	182	182	182	182	182	182	182	182	182
R-squared	0.194	0.246	0.044	0.219	0.196	0.216	0.050	0.074	0.190	0.210	0.071	0.032
Industry FE	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Year FE	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is productivity growth (g_A). Explanatory variables: vacancy rate, quits rate (Source: JOLTS), job-to-job separation rate (J2J Quits Rate; Source: Census), real investment in IPP as share of real value added (IPP/VA), real investment in non-IPP as share of real value added (Non-IPP/VA), business applications relative to real value added (Firm Apps/VA); all lagged by two year. By NAICS2 industry classification. Annual sample, 2011 to 2023.

Table 5: Panel: Labor churn, firm churn, and investment (ICT & non-ICT), 2011-2023

VARIABLES	(1) g_A	(2) g_A	(3) g_A	(4) g_A	(5) g_A	(6) g_A	(7) g_A	(8) g_A	(9) g_A	(10) g_A	(11) g_A	(12) g_A
Vacancy Rate	0.381**	0.638**	0.423**	0.815								
	(0.172)	(0.281)	(0.155)	(0.523)								
Quits Rate					0.904**	0.774**	1.279**	1.201				
					(0.425)	(0.391)	(0.570)	(1.072)				
J2J Quits Rate									0.377**	0.298**	0.989**	1.605*
									(0.150)	(0.137)	(0.354)	(0.755)
Firm Apps/VA	0.003	0.007	-0.032	0.009	-0.005	0.002	-0.026	0.019	-0.004	0.002	-0.023	0.012
	(0.011)	(0.011)	(0.023)	(0.034)	(0.012)	(0.012)	(0.026)	(0.039)	(0.011)	(0.012)	(0.022)	(0.036)
ICT/VA	0.318***	0.324***	0.371**	0.541**	0.357***	0.368***	0.378**	0.512**	0.353***	0.361***	0.268	0.519**
	(0.048)	(0.045)	(0.157)	(0.188)	(0.041)	(0.040)	(0.168)	(0.200)	(0.041)	(0.040)	(0.184)	(0.212)
Non-ICT/VA	-0.055	-0.054	0.006	-0.124	-0.070*	-0.077**	-0.008	-0.118	-0.066*	-0.073**	-0.098	-0.059
	(0.039)	(0.041)	(0.263)	(0.285)	(0.037)	(0.037)	(0.242)	(0.262)	(0.037)	(0.037)	(0.259)	(0.282)
Constant	-1.810***	-2.119***	-1.495	-2.627	-2.024***	-1.926***	-2.594*	-3.124	-2.157***	-1.943***	-4.005**	-7.421*
	(0.692)	(0.804)	(1.700)	(2.277)	(0.764)	(0.732)	(1.426)	(2.405)	(0.727)	(0.704)	(1.461)	(3.724)
Observations	182	182	182	182	182	182	182	182	182	182	182	182
R-squared	0.226	0.270	0.047	0.321	0.245	0.273	0.053	0.319	0.240	0.266	0.073	0.202
Industry FE	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Year FE	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is productivity growth (g_A). Explanatory variables: vacancy rate, quits rate (Source: JOLTS), job-to-job separation rate (J2J Quits Rate; Source: Census), real investment in ICT as share of real value added (ICT/VA), real investment in ICT as share of real value added (ICT/VA), business applications relative to real value added (Firm Apps/VA); all lagged by two year. By NAICS2 industry classification. Annual sample, 2011 to 2023.

Table 6: Panel: Teleworkability, churn, and investment (ICT), 2011-2023

VARIABLES	(1) g_A	(2) g_A	(3) g_A	(4) g_A	(5) g_A
Telework	0.023**	0.024*	0.003	0.017	0.015
	(0.012)	(0.012)	(0.010)	(0.011)	(0.010)
Telework x post-2019		-0.001	0.013	0.007	0.001
		(0.028)	(0.023)	(0.022)	(0.023)
Vacancy Rate			0.736***		
			(0.247)		
Quits Rate				1.009***	
				(0.385)	
J2J Quits Rate					0.367***
					(0.128)
Firm Apps/VA			0.009	0.005	0.005
			(0.011)	(0.012)	(0.012)
ICT/VA			0.287***	0.313***	0.310***
			(0.041)	(0.039)	(0.039)
Constant	-1.077*	-1.092*	-2.682***	-3.279***	-3.082***
	(0.637)	(0.655)	(0.803)	(0.861)	(0.785)
Observations	182	182	182	182	182
R-squared	0.049	0.043	0.264	0.271	0.261
Industry FE	N	N	N	N	N
Year FE	Y	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is productivity growth (g_A). Explanatory variables: Dingel-Neiman teleworkability index (Telework), vacancy rate, quits rate (Source: JOLTS), job-to-job separation rate (J2J Quits Rate; Source: Census), real investment in ICT as share of real value added (ICT/VA), business applications relative to real value added (Firm Apps/VA); all lagged by two year (except Telework). By NAICS2 industry classification. Annual sample, 2011 to 2023.

Productivity growth and Business Applications, Cross-sectional

So far, we haven't found much evidence for a positive association between firm churn, as measured by business applications, and productivity growth. Figure 7 shows an upward jump in business formation in 2020. We want to see if it can account for productivity growth in the cross-section since the pandemic.

Table 7: Cross-sectional: Business formation and investment

VARIABLES	(1) g_A 2015-2019	(2) g_A 2015-2019	(3) g_A 2015-2019	(4) g_A 2020-2023	(5) g_A 2020-2023	(6) g_A 2020-2023
Business Apps 15-19	-0.161	-0.157	-0.111			
	(0.100)	(0.104)	(0.093)			
IPP/VA 15-19		0.084				
		(0.079)				
ICT/VA 15-19			0.227***			
			(0.058)			
Business Apps 20-21				0.182**	0.187**	0.169**
				(0.080)	(0.074)	(0.072)
IPP/VA 20-22					0.171***	
					(0.030)	
ICT/VA 20-22						0.172***
						(0.045)
Constant	1.859***	1.206*	0.557	-1.976	-3.445**	-2.690*
	(0.499)	(0.622)	(0.464)	(1.463)	(1.477)	(1.382)
Observations	39	39	39	39	39	39
R-squared	0.049	0.126	0.506	0.148	0.304	0.257

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is productivity growth (g_A), average of 2015 to 2019 and 2020 to 2023, respectively. Explanatory variables: average annual growth rate in business applications (Business Apps) of 2015 to 2019 and 2020 to 2021, real investment share in IPP (ICT) as share of real value added (IPP/VA and ICT/VA, respectively), average of 2015 to 2019 and 2020 to 2022.

The cross-sectional correlations of business applications growth jointly with IPP and ICT investment are summarized in Table 7. Columns 1 to 3 show that for the period of 2015 to 2019, there is no positive association between business applications and productivity growth. Columns 3 to 6 show that the result is different once we focus on the growth in business applications in 2020 and 2021, the period in which the major spike in business applications since the pandemic happened. An industry with a one percentage point increase in the average growth rate of business applications is associated with a 0.17 to 0.18 percentage point increase in annual productivity growth, depending on the specification. Columns 5 and 6 show that the results hold even if we condition on IPP and ICT investment, respectively. The (unweigthed) industry average growth rate of business application in 2020 and 2021 is 15 percent, while it is 2.9 percent from 2015 to 2019.

Panel results: Investment on Churn

Do we see any relationship between ICT/IPP investment rates and the degree of labor churn across industries? Table 8 and 9 summarize the correlation between the two variables. Overall, IPP/ICT investment was somewhat less intensive in industries with higher quits, possibly reflecting higher pandemic-related uncertainties. However, the estimated magnitudes are not large and the correlation is not consistent across different measures of churn.

Table 8: Panel: Investment (IPP) and labor churn

VARIABLES	(1) IPP/VA	(2) IPP/VA	(3) IPP/VA	(4) IPP/VA	(5) IPP/VA	(6) IPP/VA	(7) IPP/VA	(8) IPP/VA	(9) IPP/VA
Vacancy Rate	0.037	-0.143*	-0.143*						
	(0.032)	(0.074)	(0.074)						
Quits Rate				0.081	-0.359**	-0.343**			
				(0.119)	(0.143)	(0.149)			
J2J Quits Rate							0.079	-0.028	0.005
							(0.089)	(0.265)	(0.298)
Constant	5.178***	5.884***	5.882***	5.186***	6.024***	5.991***	4.240***	4.760**	4.599***
	(1.674)	(1.679)	(0.272)	(1.718)	(1.689)	(0.312)	(1.549)	(2.070)	(1.495)
Observations	45	45	45	45	45	45	48	48	48
R-squared	0.001	0.004	0.004	0.052	0.056	0.056	0.029	0.013	0.000
Industry FE	N	N	Y	N	N	Y	N	N	Y
Year FE	N	Y	Y	N	Y	Y	N	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is real investment in IPP as share of real value added (IPP/VA). Explanatory variable: vacancy rate, quits rate (Source: JOLTS), job-to-job separation rate (J2J Quits Rate; Source: Census). Annual sample, 2020 to 2022.

Table 9: Panel: Investment (ICT) and labor churn

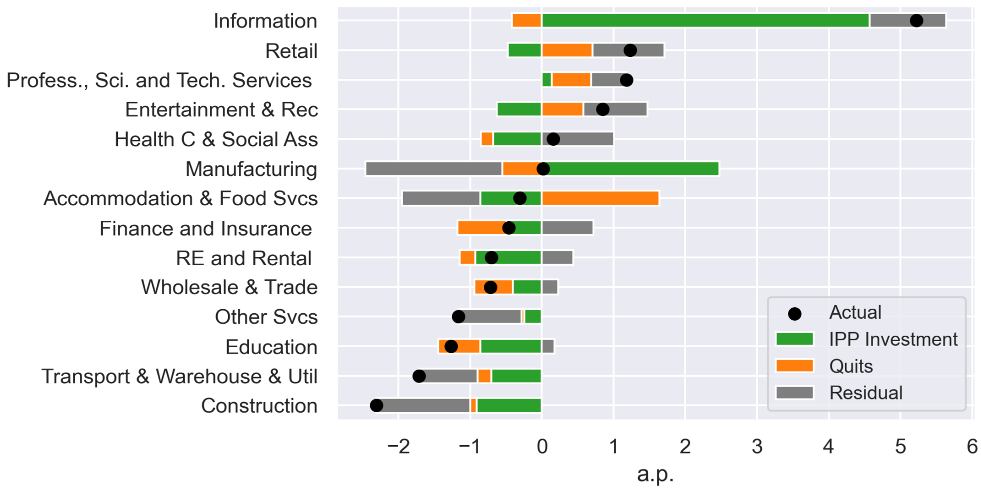
VARIABLES	(1) ICT/VA	(2) ICT/VA	(3) ICT/VA	(4) ICT/VA	(5) ICT/VA	(6) ICT/VA	(7) ICT/VA	(8) ICT/VA	(9) ICT/VA
Vacancy Rate	0.071	-0.138	-0.139						
	(0.047)	(0.094)	(0.094)						
Quits Rate				0.170	-0.406**	-0.379*			
				(0.147)	(0.196)	(0.178)			
J2J Quits Rate							0.126	-0.046	-0.019
							(0.113)	(0.311)	(0.374)
Constant	4.344***	5.163***	5.168***	4.325***	5.420***	5.365***	3.988***	4.821**	4.687**
	(1.351)	(1.494)	(0.376)	(1.432)	(1.743)	(0.359)	(1.327)	(2.212)	(1.883)
Observations	45	45	45	45	45	45	48	48	48
R-squared	0.001	0.000	0.000	0.060	0.065	0.065	0.011	0.009	0.004
Industry FE	N	N	Y	N	N	Y	N	N	Y
Year FE	N	Y	Y	N	Y	Y	N	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is real investment in ICT as share of real value added (ICT/VA). Explanatory variable: vacancy rate, quits rate (Source: JOLTS), job-to-job separation rate (J2J Quits Rate; Source: Census). Annual sample, 2020 to 2022.

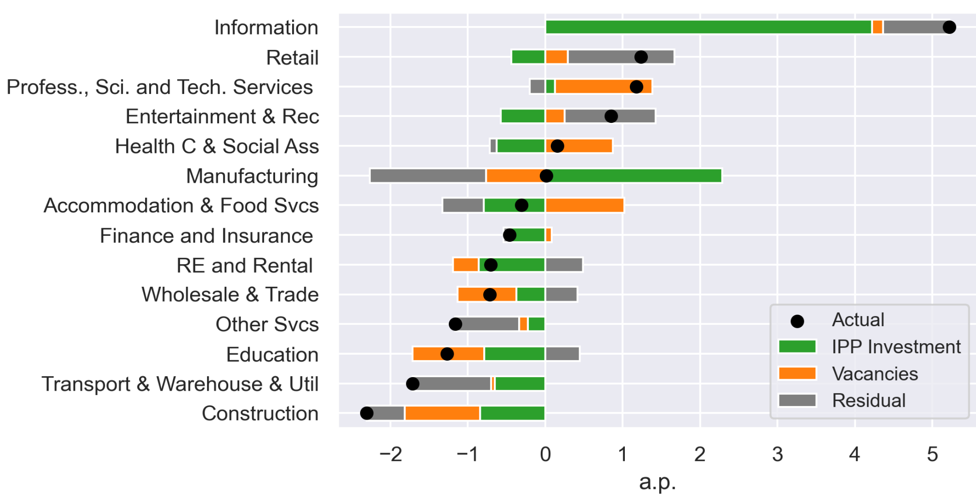
A.3 Additional Material for Section 4

Figure 13: Contributions to average productivity growth from from labor churn (quits rate) and investment, by sector



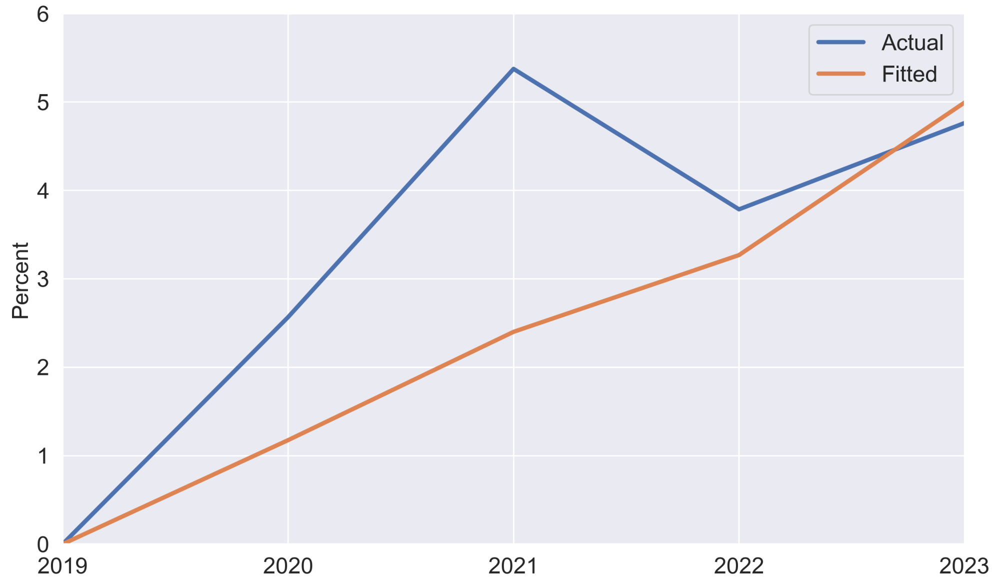
Notes: Black dot shows average productivity growth (Actual), green bar shows fitted value for real investment share in IPP capital (IPP Investment), the orange bar shows fitted value for quits rate (Quits), and gray bar is the residual. All values are averages from 2020 to 2023, in deviation from the industry average from 2020 to 2023.

Figure 14: Contributions to productivity growth from labor churn (vacancy rate) and investment, cross-sectional variation



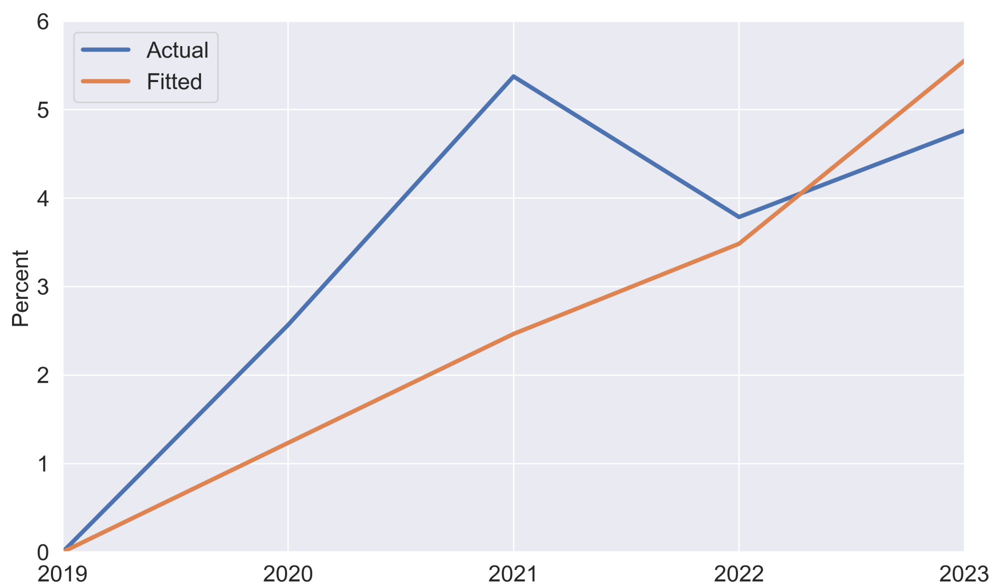
Notes: Black dot shows average productivity growth (Actual), green bar shows fitted value for real investment share in IPP capital (IPP Investment), the orange bar shows fitted value for vacancy rate (Vacancies), and gray bar is the residual. All values are averages from 2020 to 2023, in deviation from the industry average from 2020 to 2023.

Figure 15: Contributions to productivity growth from labor churn (quits rate) and investment, cross-sectional variation



Notes: Figure shows for each year the increase in productivity in percent relative to 2019, both actual and fitted value using quits rate. Actual and fitted value are aggregated by taking the weighted average of sectors, using real value added as weights.

Figure 16: Contributions to weighted average productivity growth from labor churn (vacancy rate), time variation



Notes: Figure shows for each year the increase in productivity in percent relative to 2019, both actual and fitted value using vacancy rate. Actual and fitted value are aggregated by taking the weighted average of sectors, using real value added as weights.

PUBLICATIONS

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