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PINELLAS COUNTY

ECONOMIC DEVELOPMENT

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AUTOMATION AND THE ECONOMY

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Executive Summary

The rapid rise of the automation economy is one of the hottest trends among economic developers, technologist, and futurists. Everyone agrees that it is a big deal, but no one knows what the true impact will be. Ideas have varied from a new industrial revolution ushering in a golden age to technological dystopia. The general theory is that advances such as artificial intelligence, robotics, and additive manufacturing will lead to a massive restructuring in the labor market. The reasoning is that firms, when seeking to increase output, choose between investing in capital equipment or labor. As advanced technology becomes more available and less expensive, it could be more efficient to not only supplement labor, but replace it. Thanks to a new measure, the automation index[1], it is possible to measure how likely different jobs are to be automated.

Jobs in Pinellas County roughly follow a 20-60-20 distribution pattern as approximately 20% of jobs have a low automation risk, 60% have an average risk, and 20% have a high automation risk. In general, correlations suggest that jobs requiring postsecondary education, of any variety, are generally less likely to be automated. Higher paying jobs typically are also less likely to be automated. Examining the most and least likely jobs to be automated along with assorted occupation families suggests that automation will likely effect workers who perform repetitive tasks involving physical labor. By comparison, the workers with jobs most resistant to automation are generally in fields that require creative problems solving, larger amounts of human interaction, and irregular demands.

Automation's impacts on the labor force do not appear to be demographically neutral and data suggests a disparate impact across groups. Generally, the jobs more apt to be automated are in more typically male dominated fields such as construction. Another concerning trend is that the jobs most vulnerable to automation are disproportionately staffed by minorities. Any policy interventions such as job retraining will to have to address these facts in order to tailor programs more effectively.

Policy prescriptions for how to address new structural unemployment challenges run the gamut from include universal basic income and massive public works programs to skills retraining and a libertarian position of letting the market take its course. This report seeks to remain apolitical and instead examine the local jobs in Pinellas County as to their likelihood of being automated compared with their current employment and long term projections. The most political statements in this report are that newly unemployed workers will likely need rapid job training programs and more workers, particularly men and minorities, will have to migrate into the service economy.

Occupation Families

One of the first tests used to determine how automation will affect different occupations is using analysis of variance (ANOVA). ANOVA is a statistical test that determines if a quantitative value's difference across categorical groups is statistically significant. It's a mathematical way of asking "is this number important or just random?" In a toy model looking at dog breeds by weight, ANOVA could be used to test if the difference in weight (quantitative value) between Dalmatians, Chihuahuas, and Great Danes (categorical groups) is statistically significant. In the jobs data, the automation index was tested

[1] A technical explanation of the automation index can be found in the report's appendix.

across 22 occupational families. An ANOVA test yielded a very high “f-statistic” (101.4). The f-statistic value over the number of cases demonstrates statistical significance and means it is incredibly unlikely automation risk across occupations is random. When transformed into a probability, there is less than a 1/2e16[2] chance of this being a coincidence.

Across occupations, the automation index was weighted based on 2018 employment. The average automation index for a job in Pinellas is 100.7 with a standard deviation of 15.3. This is slightly higher than the national average of 100 with a standard deviation of 15. Standard deviation, σ, is a measure of how spread out data is. A low σ value means data clumps together and a high σ means it is far apart. Pinellas County, compared nationally, has jobs that are slightly more likely to automate and that automation risk is more unevenly distributed.

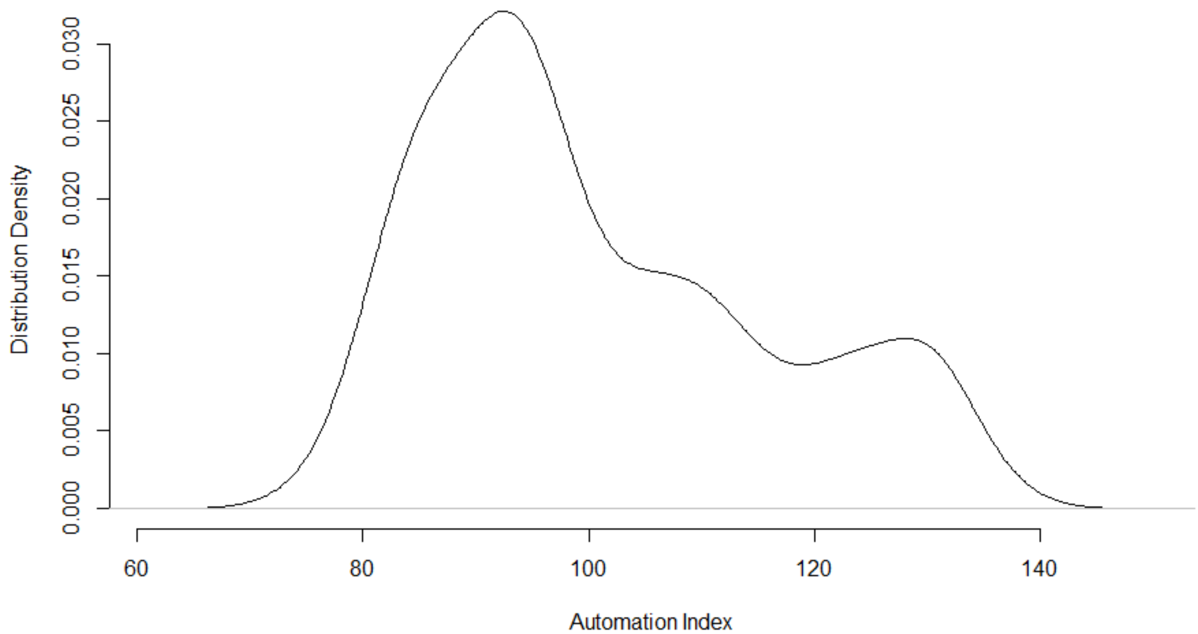
Z-scores in the table below are another method of looking at how much values differ from the mean (μ). Z-scores are a measure of how many standard deviations away from average a value is. Using the “Management Occupations” category as an example, its z-score of -1.10 means that the occupation family has an automation score 1.10σ less than the mean value and is less likely to automate.

SOC[3] Code	Description	Weighted Avg. Automation Index	x – μ	Z-score
11	Management Occupations	83.9	-16.7	-1.10
13	Business and Financial Operations Occupations	89.5	-11.1	-0.73
15	Computer and Mathematical Occupations	83.8	-16.9	-1.11
17	Architecture and Engineering Occupations	88.2	-12.5	-0.82
19	Life, Physical, and Social Science Occupations	84.7	-16.0	-1.04
21	Community and Social Service Occupations	81.6	-19.1	-1.25
23	Legal Occupations	84.7	-16.0	-1.05
25	Education, Training, and Library Occupations	85.5	-15.1	-0.99
27	Arts, Design, Entertainment, Sports, and Media Occupations	88.7	-12.0	-0.79
29	Healthcare Practitioners and Technical Occupations	88.5	-12.2	-0.80
31	Healthcare Support Occupations	96.3	-4.3	-0.28
33	Protective Service Occupations	99.0	-1.6	-0.11
35	Food Preparation and Serving Related Occupations	126.5	25.8	1.69
37	Building and Grounds Cleaning and Maintenance Occupations	122.9	22.3	1.46
39	Personal Care and Service Occupations	95.2	-5.5	-0.36
41	Sales and Related Occupations	95.8	-4.8	-0.32
43	Office and Administrative Support Occupations	98.8	-1.9	-0.13
45	Farming, Fishing, and Forestry Occupations	111.4	10.7	0.70
47	Construction and Extraction Occupations	122.5	21.8	1.43
49	Installation, Maintenance, and Repair Occupations	108.4	7.8	0.51
51	Production Occupations	113.1	12.5	0.82
53	Transportation and Material Moving Occupations	112.0	11.3	0.74

[2] $1/2e16 = 1/2^{10,000,000,000,000,000}$

[3] An explanation of SOC codes can be found in the appendix at the end of the report.

Automation in Pinellas does not exactly follow a normal distribution, or “bell curve”, but is close to it. Interestingly, the left side of the curve is much smoother with a steady transition until peaking near 90. The right side, is less even with small humps. A secondary peak near 130 is where many potentially automated jobs in field such as food services, construction, and maintenance are located.



The density distribution shows the relative proportion of jobs vs their automation score

Another way to consider the jobs in Pinellas is a table with distribution in bands surrounding the mean value. The vast majority of jobs, 63.7%, fall within one standard deviation of the mean. Using standard deviations, σ, further illustrates that the automation index is close to being normal.

Job Summary Table					
	Very Low Risk	Low Risk	Average Risk	High Risk	Very High Risk
SD Intervals	< -2σ	[-2σ, -1σ]	(-σ,+σ)	[+σ,+2σ]	> +2σ
Raw Intervals	< 70.1	[70.1,85.4]	(85.4, 116.0)	[116.0,131.2]	>131.2
N Jobs	-	75,059	295,667	73,023	20,246
%All County Jobs	0.0%	16.2%	63.7%	15.7%	4.7%
N Occupations	0	146	463	140	23
%All Occupations	0.0%	18.9%	60.0%	18.1%	3.0%

Skills, Demographics, and Automation[4]

The next step is investigating is the relationship between the automation index with economic and demographic variables. Understanding the relationship between automation and assorted social and economic factors is critical for making sense of what may happen in the labor market and planning for the future. The axiom “correlation does not equal causation” looms over this section, but correlations can be extremely valuable.

The first two variables analyzed are earnings and education. Earnings are not the same as hourly wages, but are the sum of wages, profits, taxes, and benefits. Education and earnings are used as proxies to see how high skill occupations compare with lower skill occupations. In general there is a relationship between skill, education, and earnings across the board. Good paying jobs typically pay well because the skills required to perform the jobs are rarer and often the jobs have barriers to entry. Neither education nor earnings is a perfect measure of skill, but work well enough.

Earnings & Automation Index Correlations			
	r	t	p
Median Hourly Earnings	-0.48	-14.98	<0.001
Average Hourly Earnings	-0.49	-15.57	<0.001

The correlation between hourly earnings, both on average and median, is a strong clue as to automation’s effect on the workforce. The automation index, in which higher numbers indicate jobs that are more likely to be automated, having such strong negative correlations already means that lower paid and lower skilled workers are likely to be impacted more significantly.

The next test detailed is looking at the entry level education requirements listed for occupations. Education data was recoded from categorical values (e.g. “Associate’s Degree”) into dummy variables. Using dummies, binary pairs of 0 and 1, makes it possible to test education levels in a straightforward fashion. Dummies were created in which a 1 was coded for occupations requiring any post-secondary education and also for occupations that require a bachelor’s degree or higher.

Education & Automation Index Correlations			
	r	t	p
Any Post-Secondary	-0.68	-26.02	<0.001
Bachelor's or More	-0.66	-24.07	<0.001

[4] The following tables use r, t, and p values to measure relationship between the automation index and other variables. These are descriptive statistical values. Pearson’s r, also known as the correlation coefficient ranges from -1 to 1. -1 means there is a perfectly negative correlation between two values, 0 means there is no relationship, and 1 there is a perfectly positive relationship. Student’s t-statistic, measures the statistical significance of a relationship between variables. A t value greater larger than 2 or less than -2 means that a relationship between variables likely is not by chance. The p value is the probability that the relationship between variables is a false positive.

The relationship between education and automation is even stronger than the relationship between earnings and automation with more impactful r and t values. The trend is automation poses a greater risk to lower skill positions, particularly the least educated workers.

Occupational automatization does not appear to be a race or gender neutral process. Regardless of the reason, men and women along with whites and non-whites are found in different proportions across occupations. Potentially lurking variables are at play in this process and could explain other causes, but demographically it appears automation will affect men and people of color.

Demographics & Automation Index Correlations			
	r	t	p
%Male	0.39	11.81	<0.001
%Non-White	0.30	8.78	<0.001

What is likely happening is that male dominated industries such as construction, manufacturing, and maintenance have greater automation risk than generally female dominated occupations like social services, education, and healthcare. The result is male are picked up as a risk factor. The %Non-White variable, is similar in that it shows a greater demographic risk.

A regression model was built to test the effect demographic factors have on automation risk. Several models were tested and all showed statistical significance. The model with the greatest fit on existing data is:

Automation Index = A + β_1*Average Hourly Earnings + β_2*Postsecondary Education + β_3*%Male + β_4*%Non-White

With a summary output of:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	94.11011	1.69078	55.661	< 2e-16
Avg. Hourly Earnings	-0.24681	0.02757	-8.951	< 2e-16
Post-Secondary Education	-13.24201	0.91073	-14.540	< 2e-16
%Male	19.44626	1.40796	13.812	< 2e-16
%Non-White	19.84677	2.84533	6.975	6.6E-12

The adjusted R-squared value in the model is 0.597. 59.7% of the automation index's variance can be attributed to these four factors. The estimate column is where the regression coefficient, β, values from each variable are located. %Male and %Non-White variables have large coefficients because the percentage values range from 0 to 1. The Post-Secondary Education variable is a binary that is either 0 or 1. The negative regression coefficients on Avg. Hourly Earnings and Post-Secondary Education mean that jobs requiring higher education and jobs earning more are less likely to automate. The positive coefficients on %Male and %Non-White mean that occupations with higher percentages of male and minority workers are more likely to automate.

Job Projections

SOC	Description	Weighted Automation Index	2018 Jobs	2028 Jobs	Job Change	%Change
11	Management Occupations	83.9	22,032	24,258	2,226	10.1%
13	Business and Financial Operations Occupations	89.5	28,033	30,373	2,340	8.3%
15	Computer and Mathematical Occupations	83.8	13,264	14,418	1,154	8.7%
17	Architecture and Engineering Occupations	88.2	5,483	5,574	91	1.7%
19	Life, Physical, and Social Science Occupations	84.7	2,430	2,803	373	15.3%
21	Community and Social Service Occupations	81.6	6,808	7,631	823	12.1%
23	Legal Occupations	84.7	4,823	5,263	441	9.1%
25	Education, Training, and Library Occupations	85.5	17,911	19,016	1105	6.2%
27	Arts, Design, Entertainment, Sports, and Media Occupations	88.7	8,128	8,516	388	4.8%
29	Healthcare Practitioners and Technical Occupations	88.5	32,582	36,324	3,742	11.5%
31	Healthcare Support Occupations	96.3	16,319	18,774	2,455	15.0%
33	Protective Service Occupations	99.0	9,654	9,974	321	3.3%
35	Food Preparation and Serving Related Occupations	126.5	46,874	52,270	5,396	11.5%
37	Building and Grounds Cleaning and Maintenance Occupations	122.9	17,024	18,274	1,249	7.3%
39	Personal Care and Service Occupations	95.2	16,615	18,427	1,812	10.9%
41	Sales and Related Occupations	95.8	53,847	54,767	920	1.7%
43	Office and Administrative Support Occupations	98.8	80,46	82,133	2,087	2.6%
45	Farming, Fishing, and Forestry Occupations	111.4	569	586	16	2.9%
47	Construction and Extraction Occupations	122.5	19,451	21,368	1,917	9.9%
49	Installation, Maintenance, and Repair Occupations	108.4	18,627	19,515	887	4.8%
51	Production Occupations	113.1	23,835	22,127	-1,707	-7.2%
53	Transportation and Material Moving Occupations	112.0	19,642	20,485	817	4.2%
	All Pinellas County Jobs	100.7	463,994	492,851	28,857	6.2%

In the above table, occupational families with high automation risk are highlighted in orange and low risk are highlighted in green. Green fields have an automation score at least one σ below the average and orange fields are at least one σ above average. The regression model holds as many of the green fields are high paying, high skill, and cognitive reasoning heavy. Even outside of high skill occupation groupings, other lower skill service sector fields are generally at lower risk. The service sector, with its emphasis on working with people and ideas, generally has less risk than occupations working with things. All of the orange fields are very "thing oriented" and it makes sense that repetitive manual tasks are simpler to automate.

Looking at the job growth projections between 2018 and 2028, there is an immediate contradiction. Some of the occupational families most likely to automate also have some of the highest projected job growth. Emsi's model cannot predict when occupations will automate and instead relies on previous job growth to predict future growth. As a result, the above table is generally a "rough guide" to the future and not absolute. Optimistically, this may not be a huge issue. Emsi projects Pinellas County will only have modest job growth because 2018 data starts in a tight labor market. Baby Boomers retiring will also put downward pressure on the workforce's size. Assuming the labor market remains relatively tight because of an overall healthy economy, workers in newly automated fields may be able to transition into other occupations.

Anecdotally, workforce specialists have mentioned local manufacturing plants making capital equipment investments and modernizing. This has reduced their traditional labor demand, but also created new demand for technicians and in house maintenance specialists. This trend cannot be modeled well in Emsi, but points towards a possible future. Often these new jobs have higher wages than the old jobs, but require more training.

Most and Least at Risk Occupations

Examining the ten jobs most and least likely to automate illustrates the general trends happening to the labor market. These are all occupations with at least 10 employees in Pinellas County. Eight of the ten most likely jobs to automate are construction jobs and most have no formal education requirements. Pinellas has an average hourly earnings across all jobs of $21.24 and these 10 all have earnings below the county average. In general, these are jobs that generally hit the correlations from earlier: minimal education, low earnings, more male, and more minority employment.

Occupations Most Likely to be Automated							
SOC	Description	2018 Jobs	2028 Jobs	Automation Index	Median Hourly	Avg. Hourly	Typical Entry level education
47-2042	Floor Layers, Except Carpet, Wood, & Hard Tiles	54	65	139.1	$14.84	$15.20	No formal credential
47-3015	Helpers--Pipelayers, Plumbers, Pipefitters, & Steamfitters	191	218	137.3	$13.83	$13.90	High school diploma
47-2171	Reinforcing Iron & Rebar Workers	49	53	137.2	$16.96	$18.78	High school diploma
35-9021	Dishwashers	2,259	2,381	136.4	$9.60	$9.96	No formal credential
47-2141	Painters, Construction & Maintenance	1,048	1,089	136.3	$14.57	$16.14	No formal credential
47-3014	Helpers--Painters, Paperhangers, Plasterers, & Stucco Masons	41	43	135.1	$9.92	$11.21	No formal credential
27-2031	Dancers	24	26	134.8	$14.22	$15.06	No formal credential
47-3013	Helpers--Electricians	589	709	134.7	$13.48	$14.17	High school diploma
47-3016	Helpers--Roofers	65	69	134.6	$12.14	$12.23	No formal credential
47-3012	Helpers--Carpenters	246	275	134.5	$10.77	$11.35	No formal credential

A concerning trend is that many of these jobs are entry level occupations and part of a career ladder. Five of the construction trades explicitly are helper positions and that can lead to master positions paying significantly more. A deeper dive into the data suggests master positions are not much more insulated from automation than the entry level positions. Regardless, if the entry level workers disappear, then there no longer will be a talent pipeline in place for the higher skill positions.

Likely what is happening in many of the above occupations is that automation will not be directly from robots, but instead from improved tools allowing each worker to increase individual output. In the construction industry, power tools have greatly increased the output per worker over time and reduced labor demand. Much of the automation in the jobs could be workers using better and more powerful tools and increased productivity further decreasing worker demand.

The most surprising observation is how highly dancers score. This is because dancers engage in physically demanding and repetitive tasks. Dancers are probably more insulated than the other occupations in the table because they provide a service as opposed to producing or manipulating physical objects. Dance as a form of expression, entertainment, and aesthetics puts it in a different category than these other jobs.

The flip side is looking Is examining the jobs the least likely to automate. There are unifying trends among these occupations too. What first jumps out is that these jobs all require higher education training. Most pay more than the county's average earnings, but surprisingly a significant number pay less.

Occupations Least Likely to be Automated							
SOC	Description	2018 Jobs	2028 Jobs	Automation Index	Median Hourly	Avg. Hourly	Typical Entry level education
27-1014	Multimedia Artists and Animators	90	96	72.2	$13.08	$17.53	Bachelor's degree
19-2012	Physicists	14	18	72.8	$61.71	$68.62	Doctoral or professional degree
19-1021	Biochemists and Biophysicists	38	44	74.6	$40.56	$47.12	Doctoral or professional degree
19-2041	Environmental Scientists and Specialists, Including Health	272	315	74.6	$24.98	$27.70	Bachelor's degree
15-2011	Actuaries	35	49	75.0	$40.56	$47.12	Bachelor's degree
19-1041	Epidemiologists	22	24	75.0	$15.86	$23.54	Master's degree
29-1022	Oral and Maxillofacial Surgeons	13	14	75.1	$102.58	$121.01	Doctoral or professional degree
11-9111	Medical and Health Services Managers	1,026	1,220	75.2	$48.20	$52.40	Bachelor's degree
21-2011	Clergy	1,025	1,248	75.3	$17.14	$18.52	Bachelor's degree
19-4093	Forest and Conservation Technicians	13	17	75.5	$15.99	$16.15	Associate's degree

Common threads among these occupations are that many require novel problem solving skills and creativity. Interestingly, these are all STEM or STEM related occupations except for clergy and multimedia artists. Multimedia artists are likely the occupation, especially compared with other artists, least at risk of automation because the work requires not only high creativity, but also the novel combination of new of different information and media. Clergy meanwhile seem like a safe because, presumably, parishioners are uncomfortable listening to sermon delivered by a robot. Furthermore, clergy are generally part of a community support network and being a priest/rabbi/imam requires counseling, community organizing, and administrative skills that go beyond leading worship services.

Conclusions

Yogi Berra once said "It's difficult to make predictions. Especially about the future." Much of this report is ultimately speculative, but raises important questions about how to best future proof the local economy. Modern workers need to be more agile than ever before as technological innovation is an accelerating process with unpredictable results. Similarly, industry will need to be adaptable in order to stay ahead of the curve.

Ideally, automation occurs during tight labor markets and causes incremental adaptation. This is the "easy" version of dealing with a changing economy. Workers released from newly automated occupations could transition to different fields with minimal friction. In the soft landing scenario, heavily automated industries pay higher wages to the remaining workers, different industries hire the newly unemployed, and lower production costs increase everyone's purchasing power. The real word is always messier than an economic model, but that is the best case scenario.

A more probable scenario is innovation happening in a more disjointedly manner with uneven fits and spurts. Sometimes the transitions will be easier, but industries may be upended during a down macroeconomic cycle. Technological innovation is unrelated to the business cycle, so it could occur either way. Technological change may be a bumpy ride, but overall is a good thing as ideas and innovation grow the economic pie.

Preparation could mean keeping track of industry trends and in order to adapt to workforce needs. Short term certifications and workforce training programs also seem to be a major component of any strategy to adjust and future proof the workforce. Keeping lines of communication open between government, workforce training and industry partners is of course another component to preparation for what may come. Educational partners obviously are another important piece of the puzzle in order to make sure communities have the right training and skills to adapt. Serving more nontraditional student populations, transitioning mid-career workers, and generally more socially and economically vulnerable populations are all ways that education and workforce training may have to adopt to the automation age.

Appendix – Technical Notes and Methods

Automation Index: This report uses an automation index value derived from occupation skills listed in the Occupation Information Network (O*NET) and attached to SOC codes by Emsi. O*NET is a database developed by the US Department of Labor that has skills, interests, educational information attached to occupations. Emsi is an economic modeling program that synthesizes public and private data to create regional economic models with industrial and occupational information. Emsi's automation is index centered at 100. Jobs with higher values are more likely to be automated and jobs with lower scores are less likely to be automated. Occupations are assigned scores based on the time spent on tasks at work. Occupations spending more time on repetitive tasks that are likely to be automated were assigned higher automation index values.

SOC: Analysis is based on Standardized Occupational Classification System (SOC) codes. SOC is a counterpart to North American Industrial Classification System (NAICS). NAICS is a top down approach to the economy and SOC is the bottom up counterpart. SOC is a classification system that iteratively categorizes employees based on their roles in companies. Similar occupations are grouped into families with other related occupations in a way that moves general to specific. For example, code 15-0000 is for the "Computer and Mathematical Occupations" category and 15-1130 is specifically "Software Developers and Programmers." 772 of the 775 SOC codes were used for the analysis. "Unclassified Occupations," "Military Occupations," and "Legislators" were excluded because they do not have attached automation index scores.