Industry-Level Baseline Risk of COVID-19 Infection

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Industry-Level Baseline Risk of COVID-19 Infection

Taylor J. Canann, Carlos Carvalho, and Richard Lowery

Abstract: We present an industry classification–level model of economic activities in terms of (1)risk of the novel coronavirus spread and (2) economic contribution for the Austin, Texas, metropolitan area. Our measure combines various categories of activities that seem to lead to viral spread. We think these measures will provide useful information about how to ease current lockdowns and how to more efficiently put in place future lockdowns if they are needed.

JEL codes: I12, I18

Keywords: pandemic, risk measures, workplace safety

1. Introduction

In contrast to most previous public health crises, the reaction to the recent coronavirus outbreak has entailed a broad-based economic shutdown. The shutdowns appear to have been imposed without a preexisting plan or any careful analysis of the optimal approach to take in response to virus spread. In this paper, we attempt to provide a framework that can be used to inform the decisions about the best path for relaxing the shutdown, to determine a more efficient approach for a future shutdown if the virus begins to spread again, and eventually to evaluate the effectiveness of the measures taken in response to the initial outbreak. Specifically, our goal is to use available data about different economic activities to rank those activities on the basis of risk of virus transmission. We also calculate the economic contribution of each activity to the economy of the Austin, Texas, area where we are based, so that decision makers can weigh the costs and the benefits of shutdowns and alternative virus-suppression policies.

We propose a potential measure of infectious risk for each industry called the baseline risk measure, which intends to capture the risks of virus spread of different activities in the absence of mitigation measures. The measure is a nonlinear relation between the following five contagion factors: (1) proximity to other individuals (proximity measure), (2) exposure to disease and infections (exposure measure), (3) working in an enclosed vehicle with or without other people (enclosed vehicle measure), (4) contact with other people (contact measure), and (5) time spent indoors versus outdoors (indoor/outdoor measure). These measures are derived from responses to the O*Net Survey (US Department of Labor 2019).

This metric should allow municipalities or states to weigh the tradeoff between public health and economic costs of resuming or shutting down different economic sectors. The current model of dividing activities into "essential" versus "nonessential" fails to consider such tradeoffs and likely leads to higher costs for the same level of public health protection than would a more tailored approach. Further, the current approach appears to be unsustainable even in the relatively short term, so development of a better-designed program is imperative.

This paper, after the introduction, is presented as follows: section 2 describes how the contagion factors are calculated. The main finding of the paper, the baseline risk measure, is computed in section 3. In sections 4 and 5, we build up the industry-specific age distributions and digitization scores. We then analyze how the baseline risk measure relates to GDP and employment in the Austin metropolitan statistical area (MSA) in section 6, and we measure the shifts in unemployment and unemployment insurance claims in section 7. Then, in section 8, we discuss our identification scheme for the baseline risk measure. Section 9 concludes. For cities in Texas but outside Austin, we have developed an online supplement to provide equivalent economic measures.[1]

[1] This supplement can be found at https://sites.google.com/view/salemcentercovid/home.

2. Five Factors of Risk

Our objective is to construct a measure that has a sufficient structural interpretation so that it can address the events that lead to a risk of virus spread. For that reason, we focus on a relatively large number of survey questions. We attempt to relate them to each other in such a way as to generate some measure of the total risk. Crucially, current clinical understanding of the virus is insufficient to pin down the weights on the various components of our measures, so the current risk ranking must be viewed as preliminary. Further, our measure is intended to permit identification of the underlying parameters on the basis of demographic characteristics of infected individuals, a dataset we hope will become available before future shutdowns are considered.

We base the construction of our measure on the current recommendations for virus mitigation; although to our knowledge those recommendations have not been fully validated, they represent the consensus understanding of how the virus spreads. For example, although it is possible that being close to an infected person does not raise the chance of getting infected, that conclusion would seem highly implausible under the germ theory of disease. Thus, we treat proximity to and contact with other individuals as a source of risk. We also include exposure to infectious diseases as a risk factor for similar reasons. On the basis of initial medical evidence (Qian et al. 2020), we also conjecture that indoor transmission is appreciably more likely than outdoor transmission.

Our first step is to define and calculate five contagion factors for each of the professions listed on the O*Net Survey (US Department of Labor 2019). The questions we use for the factors are listed in appendix A. The proximity measure, the exposure measure, and the enclosed vehicle measure are directly taken from individual questions in the survey, and each takes a value between 1 and 5. However, we compute the contact measure and the indoor/outdoor measure by combining three and five questions, respectively. Once we calculate a profession score, we calculate the industry measure by taking a weighted average of the profession factor weighted by the number in each profession. We match the professions to the North American Industry Classification System (NAICS) codes.

Now we will consider the indoor/outdoor measure. We first create an indoor measure and an outdoor measure from the respective survey questions by taking the maximum in each category. We do so because we are concerned with what the individual profession does, and we do not want to penalize members of that profession for not participating in the other indoor or outdoor activities.

Using these data, we can determine the indoor/outdoor measure by dividing the indoor measure by the outdoor measure to obtain an indicator that models that outdoor activities are less risky than indoor activities:

$$\frac{Indoor}{Outdoor} Measure = \frac{5}{6}\left(\frac{Indoor}{Outdoor} + 1\right).$$

This indoor/outdoor measure is normalized to take a value between 1 and 5 for each profession; following this, the weighted average is calculated for each industry as discussed previously.

The final risk factor measure is the contact measure. This measure is the average contact score of the three responses that were given by each profession. Each of the questions gives different types of contact that may contribute to contagion. Ideally, we can eventually weight those types of contact by their contribution to overall risk of infection, but we do not currently have adequate medical information to construct such weights.

3. Baseline Risk Measure

We can now describe and calculate the baseline risk for each industry as a nonlinear combination of the five factors. The baseline risk measure assumes that the two different ways to contract COVID-19 are by coming into contact with potentially diseased individuals and by working in a place that is exposed to the disease or infection.

The first step we take to get such a measurement is to estimate the amount of contact an individual has with potentially diseased individuals while he or she is at work. We call this the contact possibilities variable. The main components of the contact possibilities variable are as follows:

- Coming into contact with someone who has COVID-19 (i.e., the contact measure)
- Amplifying this measure if an individual is in contact indoors with someone who has the disease (i.e., the contact measure and the indoor/outdoor measure)
- Compounding this measure if the individual is in constant contact in a vehicle with someone who has contracted the disease (i.e., the contact measure and the enclosed vehicle measure)

Formally, the contact possibilities variable is the amount and type of contact an individual has with other people.

$$
\begin{gathered}
ContactPossibilitiesVariable = ContactMeasure \\
+\beta_1\sqrt{Contact\,Measure * Indoor/Outdoor\,Measure} \\
+\beta_1\sqrt{ContactMeasure * EnclosedVehicleMeasure}.
\end{gathered}
$$

Note the functional form of this component of the measure; being outdoors more results in a lower risk, but only when the individual interacts with other people. That is, our measure is designed to capture (a) that being in contact with more people is worse than being in contact with fewer people and (b) that contact inside is worse than contact outside, but (c) that being inside itself is not a risk factor. This specification is for our preliminary understanding of the spread of this particular virus; it would not be valid, for example, as a model of measles transmission, where entering a room that has been vacated by an infected individual is actually a potential source of risk. We parameterize the indoor-outdoor interactions with β_1 and β_2, where β_2 captures the measure of being in an enclosed vehicle versus otherwise indoors. For our initial measure construction, we set $\beta_1 = \beta_2 = 1$. At this stage, we cannot determine the correct values for those weights, so we use the simple equal weights as a baseline and present the results for other weights in appendix B. Ultimately, the appropriate values for the parameters should be identified from infection data; see section 8.

Further, evidence strongly suggests that the key to spreading COVID-19 is being close to other people. Therefore, if an individual is in contact with people but not close to any of them, then that person has little chance of contracting the disease. So we need to multiply the proximity measure variable by the contact possibilities variable to obtain an estimate of the ability for the disease to spread, as follows:

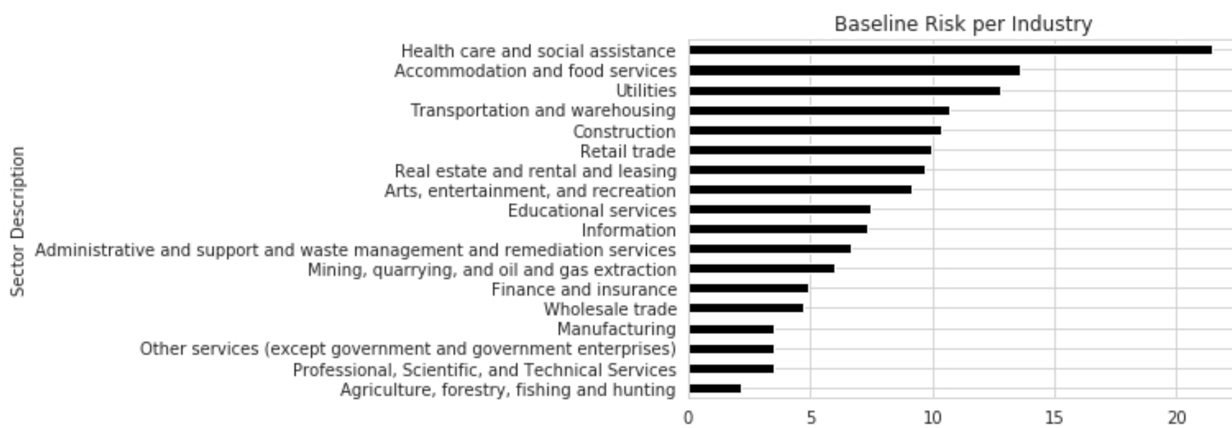
$$ContactSpreadVariable = ProximityMeasure \times ContactPossibilitiesVariable.$$

Another factor in disease spread is working in an environment that has a high level of exposure to disease and infection. To account for this factor, the proximity measure and the exposure measure are combined additively; if individuals are exposed to diseases regularly at the workplace, then they should be considered to be at higher risk of contracting the infection, all else held constant. The idea is that, regardless of contact, workers who are routinely exposed to disease are operating at a higher level of risk; our measure effectively puts such workers on a higher parallel plane on the basis of the exposure measure. An interaction term with contact or a quadratic form might be more appropriate; however, the vast majority of high-exposure workers are in healthcare or custodial positions, which are already high-risk professions and cannot be shut down readily. Thus, we maintain an additive form because this measure will not interact much with other sources of risk for most professions. So, taking the contact spread variable, we add the exposure measure, and subtract 30 (as a normalization) to obtain the baseline risk measure for each industry.

$$BaselineRiskMeasure = ContactSpreadVariable + ExposureMeasure - 30.$$

In figure 1, we present the baseline risk measurements for each of the NAICS codes listed in the United States Census.[2]

Figure 1. United States Industry-Level Baseline Risk Measurements



Note: Risk of contracting COVID-19 at the workplace owing to the five factors of risk listed in section 2.
Source: Authors' calculations based on data from O*Net Survey (US Department of Labor 2019).

[2] These codes are presented to match data in section 6.

Here, we would like to clarify some interesting points in the data shown in figure 1. First, why is educational services a relatively low-risk activity? This situation arises because all postsecondary educators are included in the measure, which lowers the average measure. When considering the educational sector without postsecondary education, the risk is slightly higher. Also, it is notable that construction has a relatively high score, but all construction subfields are not equally risky. Construction is pulled up in the risk factor by subfields such as tilers and carpenters who have contact with people and who work more indoors while close to other workers. If we exclude those types of workers, then construction is much less risky.

Manufacturing in the United States is highly automated and thus has low proximity measures. Because of the health and safety regulations in place, the exposure measure is also very low. Finally, the transportation and warehousing industry presents significant difficulty. In this industry are some very risky professions, such as public transit or air travel, and others that are very low risk, such as signal and track switch repairers. However, the number of people working in the high-risk portion of this industry outweighs those in the low-risk portion, hence the higher score.

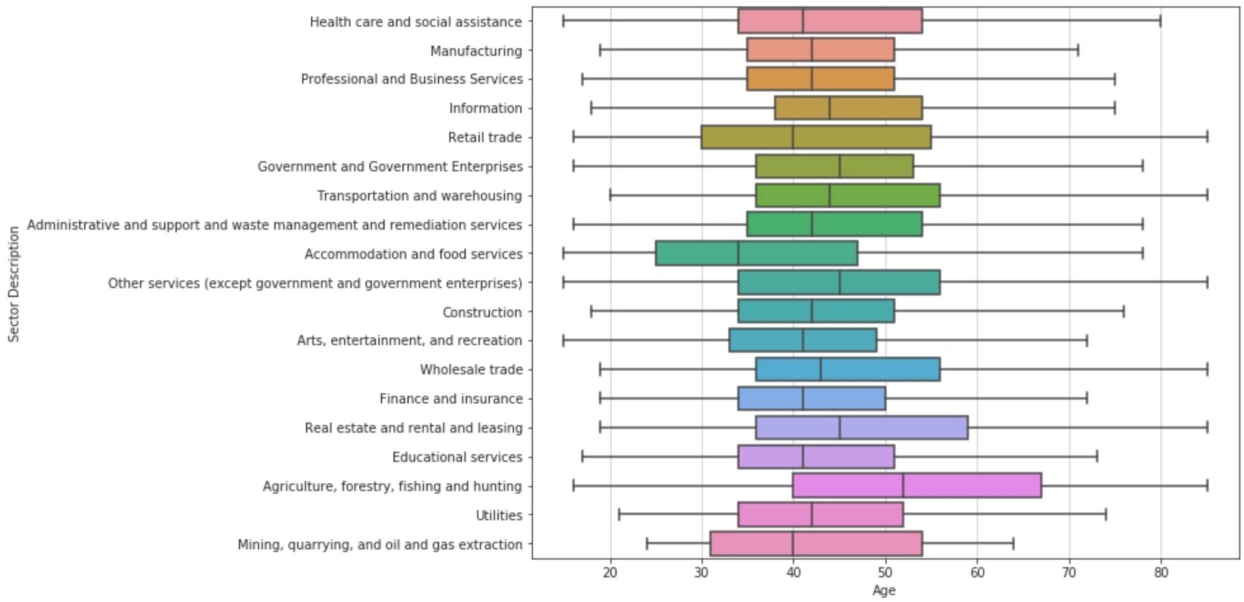
This limited set of findings suggests that our measure may provide valuable advice for reopenings and any future shutdowns. We think the measure gives a good indicator of how relatively risky individual professions and industries are with respect to virus spread.

Caveats are, of course, in order. Perhaps the most significant caveat is that we do not consider interactions between sectors. Opening one industry might lead to a very limited direct increase in spread, but it might have spillover effects in other industries. For example, certain types of office work might be low risk, but a return to office work might lead to crowding at restaurants, which could appreciably increase spread in that sector; indeed, crowding in restaurants may have a marked nonlinear relationship to spread, and this element is not captured in our risk measure. Such types of follow-on effects emphasize the need for further analysis of interconnectivity among industries, but evidence of this interconnectivity is not accessible from the O*Net data. Currently, we are creating a cross-industry elasticity measure to estimate the spillover effects to address such concerns. More important, as openings proceed, such considerations should motivate the data collection that is undertaken through contact tracing, random testing, and other surveillance measures.

4. Industry-Level Age Distributions

In this section, we present the age distribution in industries, gathered from the American Time Use Survey via the Bureau of Labor Statistics (2018). Figure 2 presents this distribution. At an individual level, age appears to be the most important risk factor, both directly and through the correlation between age and dangerous comorbidities. Although the distribution of age by profession does not show a great deal of variability, there are a few standout industries to note. Mining, quarrying, and oil and gas extraction not only have a relatively young age distribution but also are almost completely devoid of workers older than 65; that is, hardly anyone at greatest danger from COVID-19 works in this industry. Thus, according to our measures, such activities should probably continue under any scenario. Other considerations that cannot be addressed by our model must, of course, play a role in such decisions. In particular, the mining share of this activity might require greater consideration, because there is a strong relationship between certain mining jobs and lung disease (Blackley et al. 2018). Thus, our results should be viewed as a starting point for ranking safety, but they do not eliminate the need for case-by-case considerations for some industries.

Figure 2. Age Distribution for Each Industry in the United States



Note: Each standard box plot starts by describing the median age of the industry that ranges from 34 in accommodation and food services to 52 in agriculture, forestry, and fishing and hunting. The distribution of ages between the first and third quartiles are depicted by the mass around the median. Last, the whiskers give the minimum and maximum ages for each industry. All outliers, which are defined to be 1.5 times the interquartile range, have been dropped from the figure but not from the data.

Source: Bureau of Labor Statistics (2018)

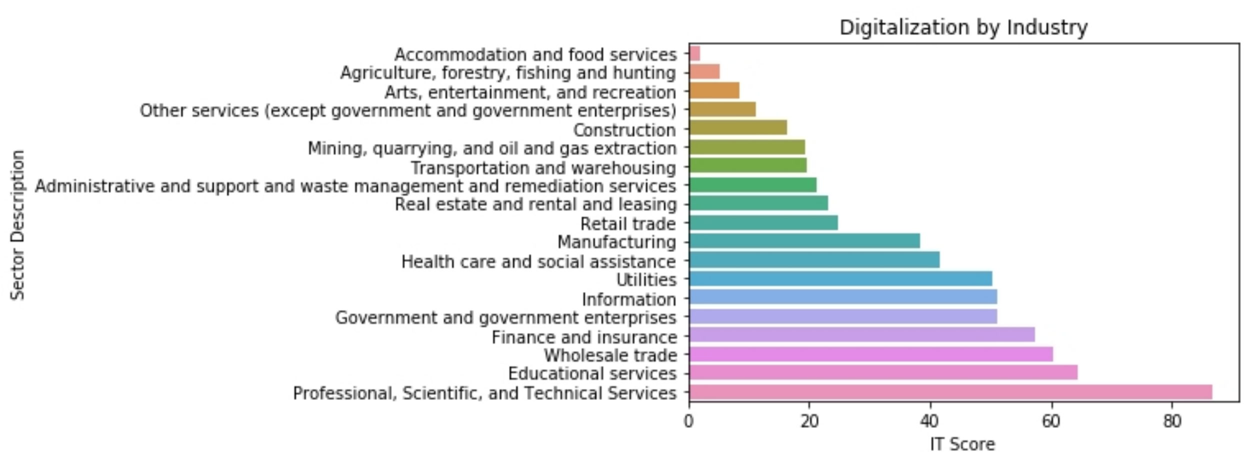
The age profile of mining, quarrying, and oil and gas extraction contrasts somewhat with other, younger professions. For example, the accommodation and food services category has an appreciably lower average age, but there is a nontrivial tail of older workers who may be at risk. Thus, opening this industry is probably safe but only when careful attention is paid to isolating or continuing not to employ vulnerable workers.

In contrast, the agricultural workforce appears to skew older. We expect this fact may come in part from the undocumented or temporary status of many members of the workforce who may not have been captured in the survey. Notably, though, although agriculture appears to employ many potentially vulnerable workers, it has a very low baseline risk score; thus it probably can remain open without significant mitigation measures despite the vulnerability of the workforce. Of course, there can be no serious consideration of shutting down agriculture as a sector, but the results indicate that it may not be necessary to deploy scarce resources to mitigation in this crucial sector.

5. Digitization of Each Industry and IT Score

An important potential mitigation strategy is to rely more heavily on remote work, which is arguably easier in more digitized industries (figure 3). Thus we report the scaled-down (we subtract 48) version of the IT score from Gallipoli and Makridis (2018). As this measure addresses mitigation efforts, we do not integrate it into our baseline risk measure, which is intended to capture the risk of sectors *without* mitigation.

Figure 3. Ability to Work Remotely by Industry in the United States



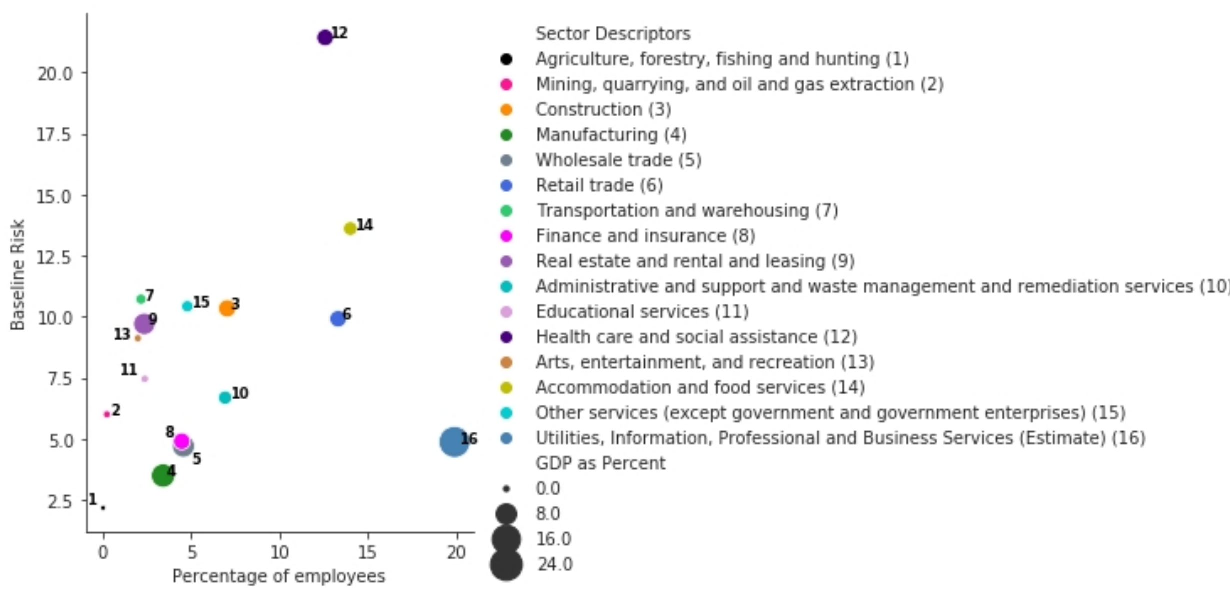
Note: The digitization measure—that is, information technology (IT) score, see —describes the digital-labor intensity of each industry that allows us to estimate how well each industry will adapt to remote work during COVID-19 lockdowns.

Source: Authors' calculations based on data from Gallipoli and Makridis (2018).

6. Tradeoffs for the Austin Economy

We now address how the baseline risk measure relates to GDP and employment, as well as what industries would most benefit a local economy if they were allowed to open. In this section, we specifically study the Austin, Texas, MSA and present the basic tradeoff between employment, baseline risk, and GDP in each industry (figure 4). To see how the Austin area compares to aggregate Texas data, we include figure 5, which aggregates over the entire state. The figures addressing the tradeoff for Dallas, Houston, San Antonio, McAllen, El Paso, and other Texas cities can be found on our website (Salem Center for Policy 2020).

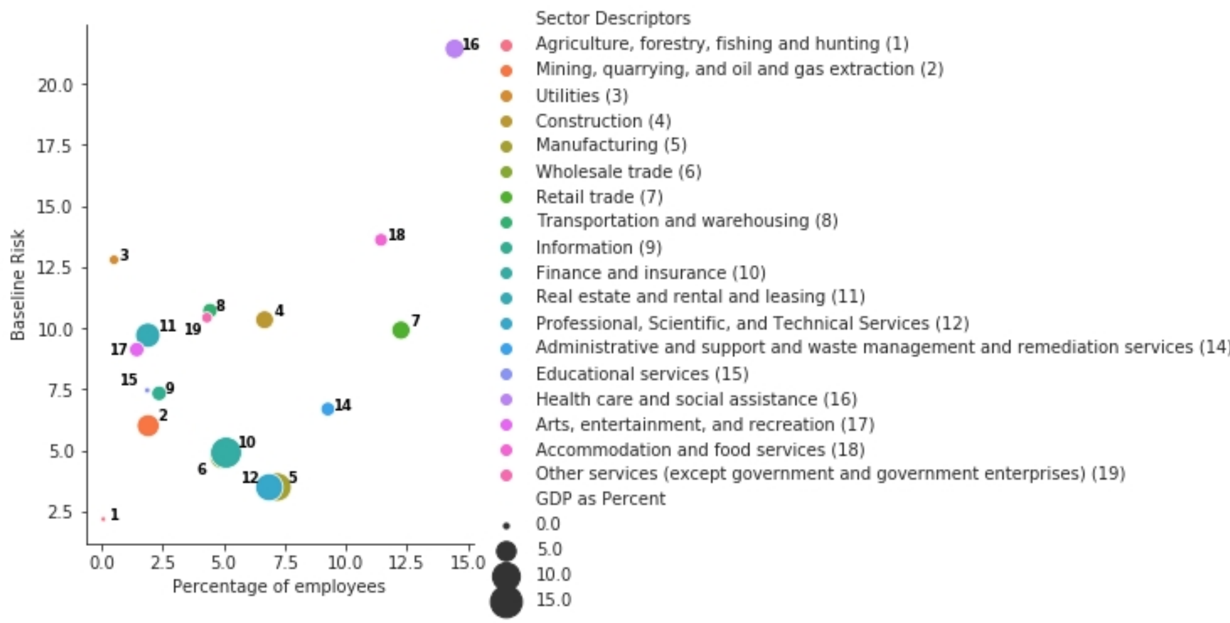
Figure 4. Austin, Texas, MSA Lockdown and Reopening Tradeoffs



Note: This plot presents the relationship between baseline risk and percentage of employees for each sector within the Austin Metropolitan Statistical Area (MSA). The magnitude of the GDP contribution is shown by the size of the marker for each industry.

Source: Authors' calculations based on data from US Bureau of Economic Analysis (2020) and the O*Net Survey (US Department of Labor 2019).

Figure 5. Texas Lockdown and Reopening Tradeoffs



Note: This plot presents the relationship between baseline risk and percentage of employees for each sector in Texas. The magnitude of the GDP contribution is shown by the size of the marker for each industry.

Source: Authors' calculations based on data from US Bureau of Economic Analysis (2020) and the O*Net Survey (US Department of Labor 2019).

Utilities, information, and professional and business services (estimate) is a low-risk industry, and allowing it to reopen would provide great benefit along economic dimensions. This finding is owing primarily to the makeup of Austin's businesses. Austin is a service economy that is heavily focused on the tech sector; thus, the ability to open up those jobs would be a large boost to GDP by allowing a large number of workers to go back to work, while not significantly increasing the risk of virus transmission. However, much of this sector may be continuing to operate remotely.

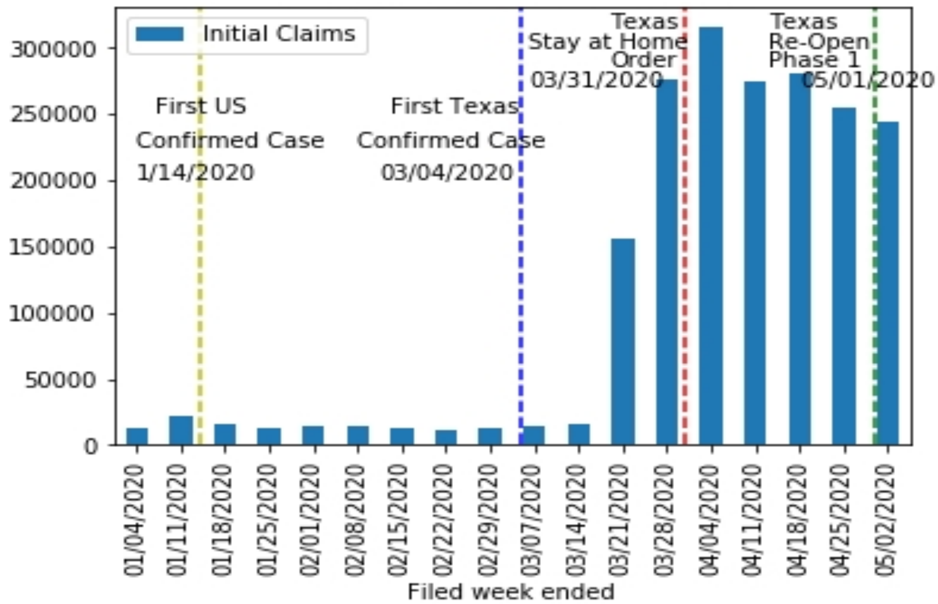
Similar arguments could be made for the financial, wholesale trade, and manufacturing industries because they are all low risk but could have a relatively large negative economic impact if they remain shut down. Wholesale trade and manufacturing sectors, in particular, are less likely to continue remotely and so should be a focus of reopening. Other industries must consider tradeoffs between safety and negative economic impacts when deciding what should open or shut. Those industries should follow best practices when reopening, because the calculation of the tradeoff will depend heavily on the effectiveness of mitigation.

7. Effect of the Shutdown

Our primary measures focus on prepandemic data so that we can understand the tradeoffs between virus spread and economic activity; yet we can also look at the realized effects of the policy response to the pandemic. Although we would like to consider the effect of policy on the GDP contribution of each sector, GDP data are collected at low frequency and with significant lags. Instead, we will consider the effects of mitigation policies on unemployment, which perhaps has the more salient effects for many individuals. We examine both the overall changes in unemployment claims in Texas and the unemployment shifts by industry in Texas and in the Austin MSA.

Figure 6 shows statewide unemployment claims. Notably, the marked increase in unemployment claims begins before the statewide shutdown order. Although this fact could arise from voluntary actions taken by individuals and businesses, please note that most of the major metropolitan areas in Texas, including Austin, instituted their own stay-at-home orders between March 21 and March 28, thereby moving ahead of the Texas order.

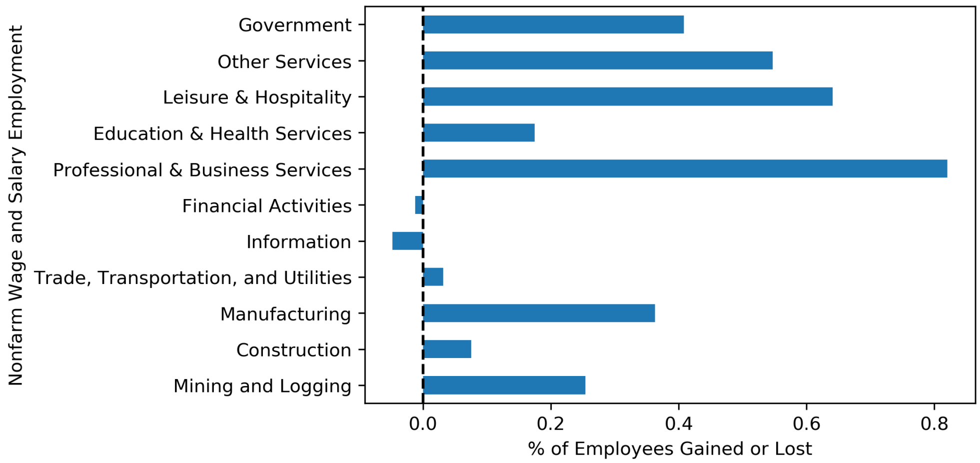
Figure 6. Texas New Unemployment Claims



Note: Weekly new unemployment claims in Texas, annotated with major statewide events.
Source: US Department of Labor (2020).

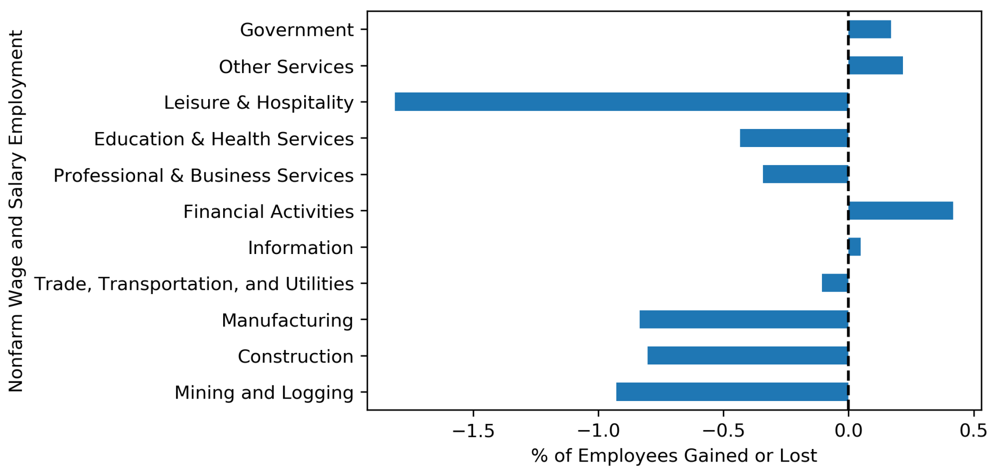
Figures 7 and 8 show the change in employment by industry for Texas as a whole; figure 7 shows the general growth in employment across sectors from January to February, whereas figure 8 shows the broad contraction between February and March. Figures 9 and 10 provide the same information for the Austin metro area; details for Dallas, Houston, San Antonio, McAllen, El Paso, and other Texas cities can be found at our website (Salem Center for Policy 2020). Employment data were obtained from the Bureau of Economic Analysis (2020).

Figure 7. Monthly Change in Employment by Industry in Texas, January to February 2020



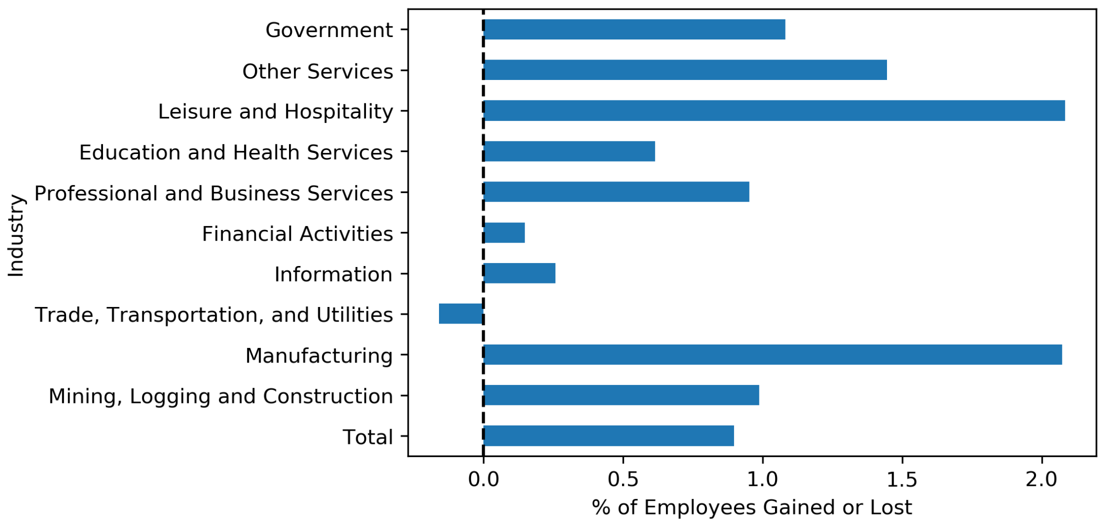
Source: Authors' calculations, which are based on US Department of Labor (2020).

Figure 8. Monthly Change in Employment by Industry in Texas, February to March 2020



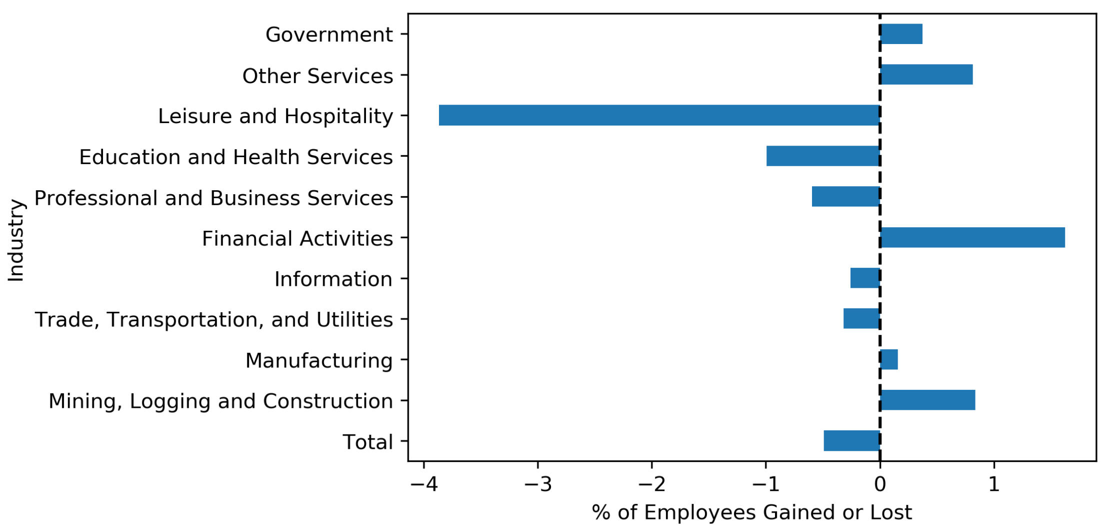
Source: Authors' calculations, which are based on US Department of Labor (2020).

Figure 9. Change in Employment by Industry in Austin MSA, January to February 2020



Source: Authors' calculations, which are based on US Department of Labor (2020).

Figure 10. Change in Employment by Industry in Austin MSA, February to March 2020



Source: Authors' calculations, which are based on US Department of Labor (2020).

Unsurprisingly, employment in almost all sectors was in obvious decline in March throughout Texas; Austin showed greater resilience in the mining, logging, and construction sector, which seems likely driven by the continuation of residential construction as an "essential activity." However, this sector suffered in Texas as a whole, possibly as a result of an indirect effect of the pandemic on the energy sector.

The employment effects at the state level line up with the growing conventional wisdom that lockdown policies have the most negative effect on working-class occupations, suggesting a greater negative impact on those who are least able to absorb economic disruption. Notably, the government sector shows no contraction. Of course, the more severe impact on working-class occupations likely results from the greater virus risk faced by those in such occupations, who will thus be more exposed to infection risk when sectors reopen. Effectively, the working-class occupations bear the risk of the virus and the costs of the shutdown, whereas the professional occupations bear far less of the costs of shutdown (because professional workers can generally work from home) but benefit from the shutdown through avoiding second-order transmission risk.

Arguably, then, the data suggest that a decentralized approach to mitigation may be more appropriate, where individuals in the riskier categories are allowed to balance the risks of the virus against the economic costs to themselves. In contrast, the original pandemic responses were designed primarily by those who benefit from mitigation but do not bear much of the economic costs.

The April unemployment statistics will reveal even more of the impact that both COVID-19 and state and local policies have had on the economy overall and in each of the MSAs. As the data are made available, they can be found in updated papers and on our website (Salem Center for Policy 2020).

8. Identification

One of our objectives in presenting this risk model is to create a framework through which real-world spread of the virus can be better understood. We are motivated in part by what we expect to be limitations on clinical work in this direction. From our understanding, the gold standard for establishing the relative importance of different transmission mechanisms involves experiments with individuals known to be unintentionally or intentionally infected. For example, a study of rhinovirus transmission was completed by having individuals play poker with an infected individual, some with and some without restraints to prevent touching of the face (Dick et al. 1987). Given the nontrivial fatality rate of the disease in question, even among less vulnerable groups, and the risk of follow-on infections, it is unlikely that such studies will be completed.

Observational studies are well underway in which individual outbreaks are carefully traced to determine the source of infection; those studies will likely be the most important source of information about spread. Once completed, the studies can be used to calibrate models like ours that seek to understand the risk of various activities. Significant uncertainties are likely to remain, however. For example, tracing strategies may tend to create a bias in favor of indoor transmission, simply because indoor contacts are more likely to be found; an infection transmitted at a restaurant is more likely to be traceable than one transmitted at a park. Thus, there remains scope for linking behavior and infection probability through an econometric model of transmission similar to what we have proposed.

To achieve econometric identification, we need data about infection by employment sector. Given those data, and assuming that nonwork activities are the same across areas, we can identify the appropriate risk weightings. It is unlikely that nonwork activities are identical across employment sectors, however, and therefore we additionally need time-use data by industry to adjust for such differences.

9. Conclusion

We have prepared and presented an industry-specific risk metric that should allow municipalities or states to determine not only what industries are the riskiest, but also what are the optimal tradeoffs when determining how to deal with the virus. As Sun Tzu wrote in *The Art of War*, "Know thy self, know thy enemy. A thousand battles, a thousand victories" (Giles 2013).

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Appendix A: Survey Questions

Here we list the survey questions that were used to calculate each of the individual measures that we used to calculate the baseline risk measurement.

Proximity measure

How physically close to other people are you when you perform your current job?

1. I don’t work near other people (beyond 100 ft.)
2. I work with others but not closely (e.g., private office)
3. Slightly close (e.g., shared office)
4. Moderately close (e.g., at arm’s length)
5. Very close (e.g., nearly touching)

Exposure measure

How often does your current job require that you be exposed to diseases or infection? This proximity can happen with workers in patient care, some laboratory work, sanitation control, etc.

6. Never
7. Once a year or more but not every month
8. Once a month or more but not every week
9. Once a week or more but not every day
10. Every day

Enclosed vehicle measure

How often does your current job require you to work in a closed vehicle or operate enclosed equipment (like a car)?

11. Never
12. Once a year or more but not every month
13. Once a month or more but not every week
14. Once a week or more but not every day
15. Every day

Contact measure

How often does your current job require face-to-face discussions with individuals and within teams?

16. Never
17. Once a year or more but not every month
18. Once a month or more but not every week
19. Once a week or more but not every day
20. Every day

How much contact with others (by telephone, face-to-face, or otherwise) is required to perform your current job?

21. No contact with others
22. Occasional contact with others
23. Contact with others about half the time
24. Contact with others most of the time
25. Constant contact with others

How important are interactions that require you to work with or contribute to a work group or team to perform your current job?

26. Not important at all

27. Fairly important
28. Important
29. Very important
30. Extremely important

Indoor/outdoor measure

Indoor questions

How often does your current job require you to work indoors in an environmentally controlled environment (like a warehouse with air conditioning)?

31. Never
32. Once a year or more but not every month
33. Once a month or more but not every week
34. Once a week or more but not every day
35. Every day

How often does your current job require you to work indoors in an environment that is not environmentally controlled (like a warehouse without air conditioning)?

36. Never
37. Once a year or more but not every month
38. Once a month or more but not every week
39. Once a week or more but not every day
40. Every day

Outdoor questions

How often does your current job require you to work outdoors, exposed to all weather conditions?

41. Never
42. Once a year or more but not every month
43. Once a month or more but not every week
44. Once a week or more but not every day
45. Every day

How often does your current job require you to work outdoors, under cover (like in an open shed)?

46. Never
47. Once a year or more but not every month
48. Once a month or more but not every week
49. Once a week or more but not every day
50. Every day

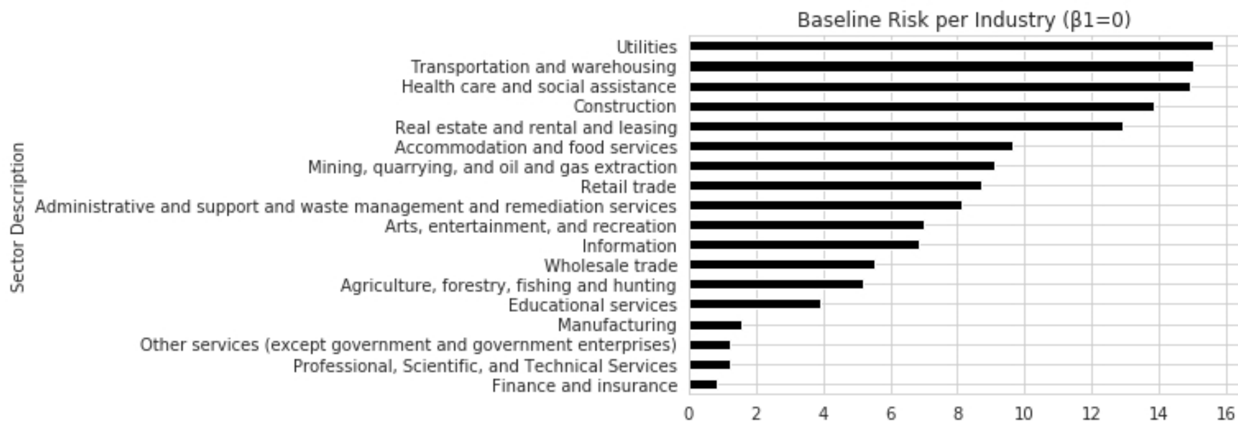
How often does your current job require you to work in an open vehicle or operating equipment (like a tractor)?

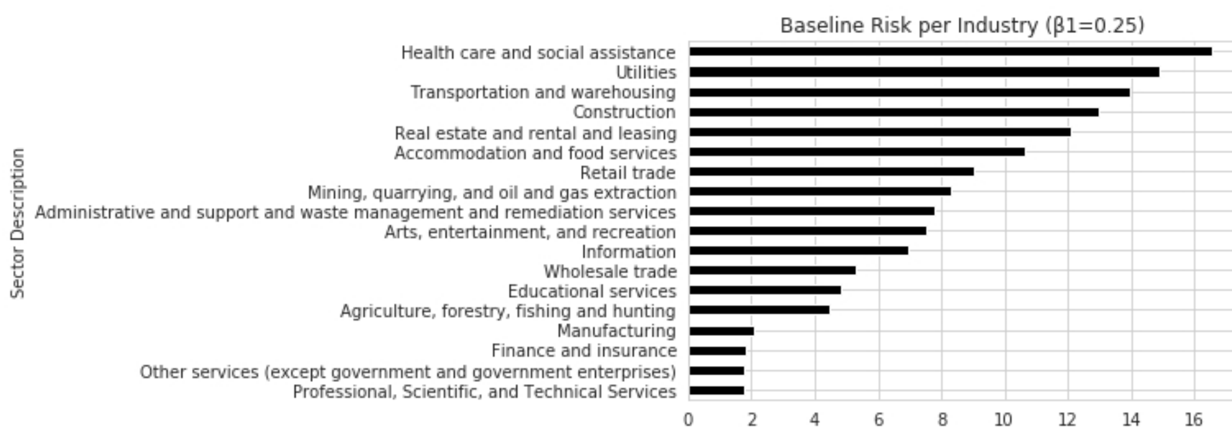
51. Never
52. Once a year or more but not every month
53. Once a month or more but not every week
54. Once a week or more but not every day
55. Every day

Appendix B: Alternative Weights

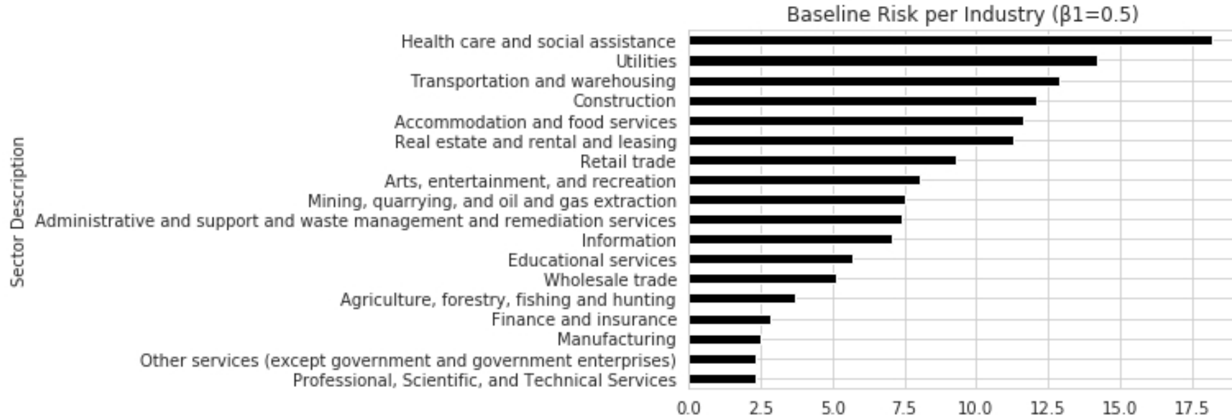
Figure B.1. 19 Alternative Weights

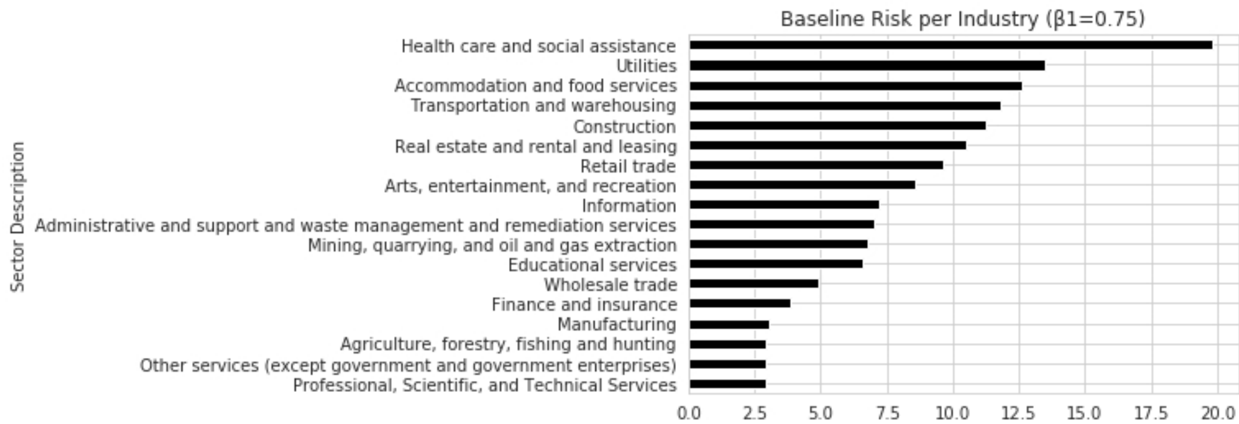
(a) Baseline Risk

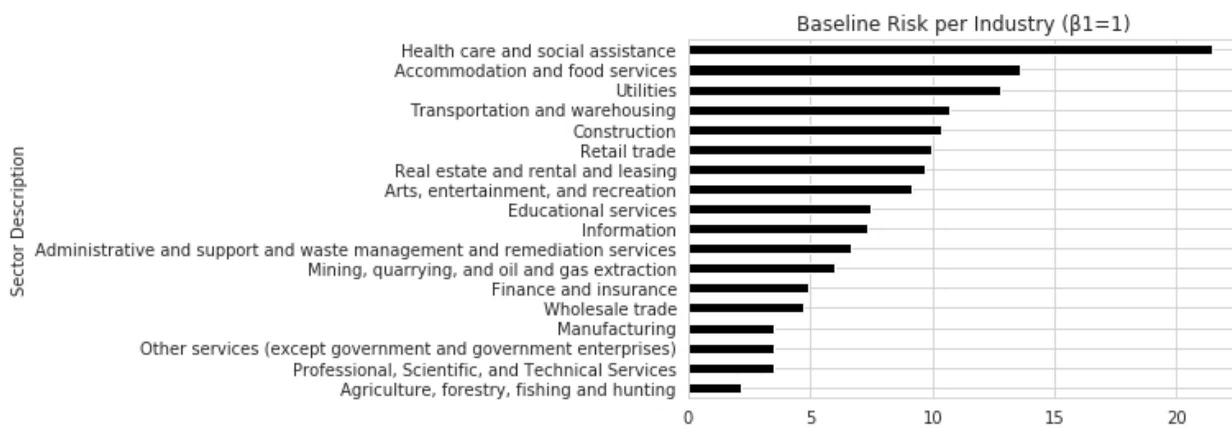




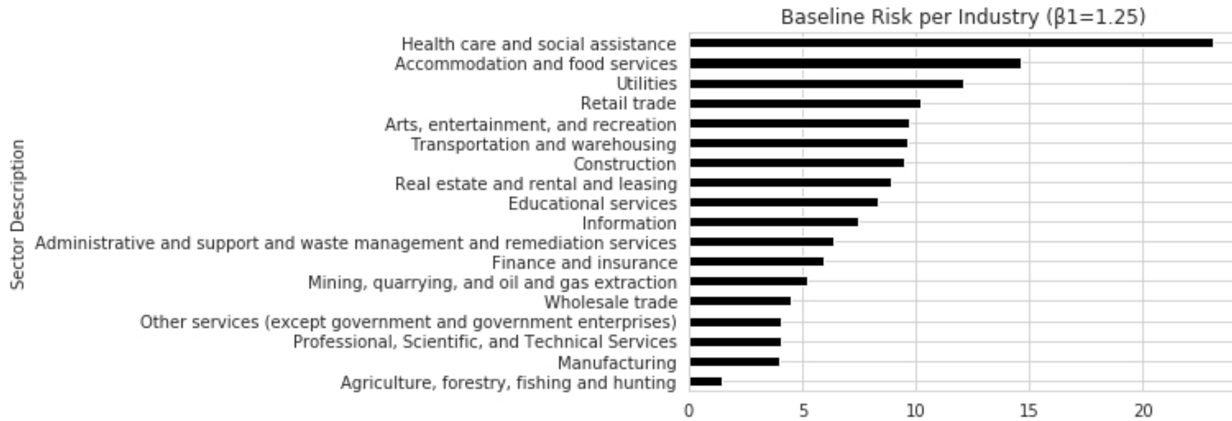
(a) Baseline Risk (cont'd.)

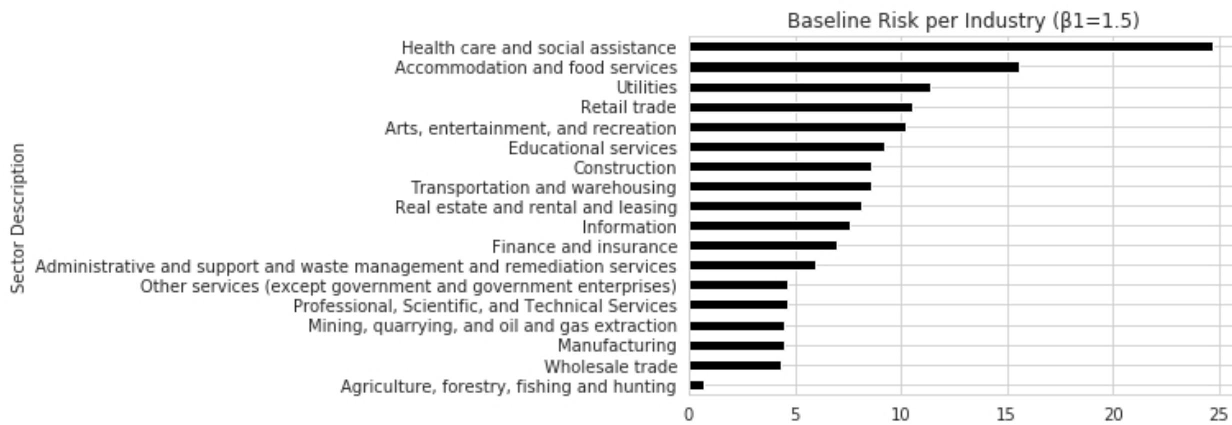


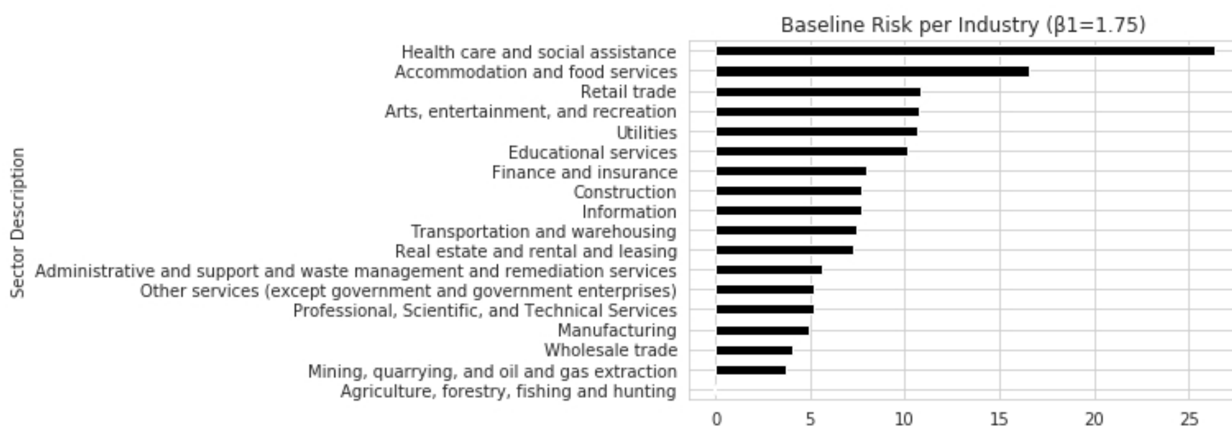




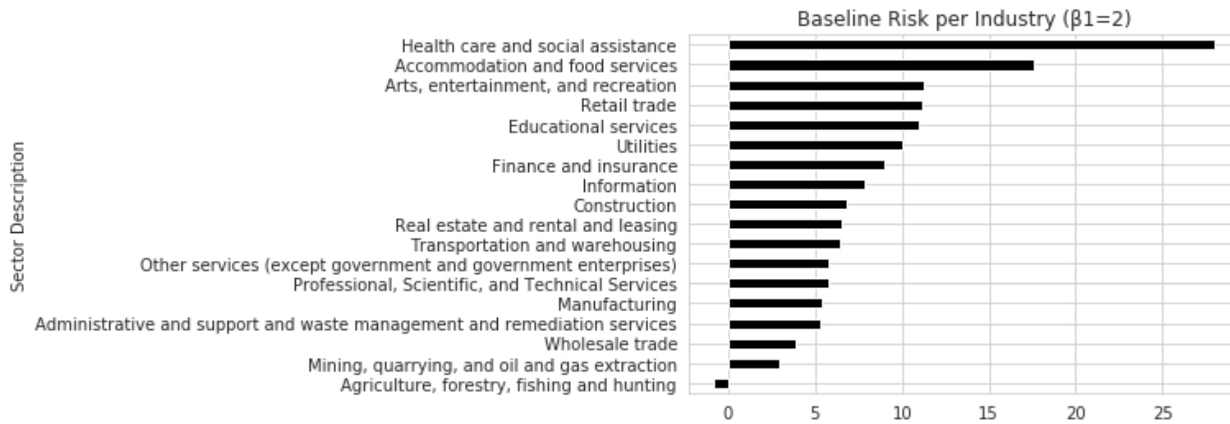
(a) Baseline Risk (cont'd.)





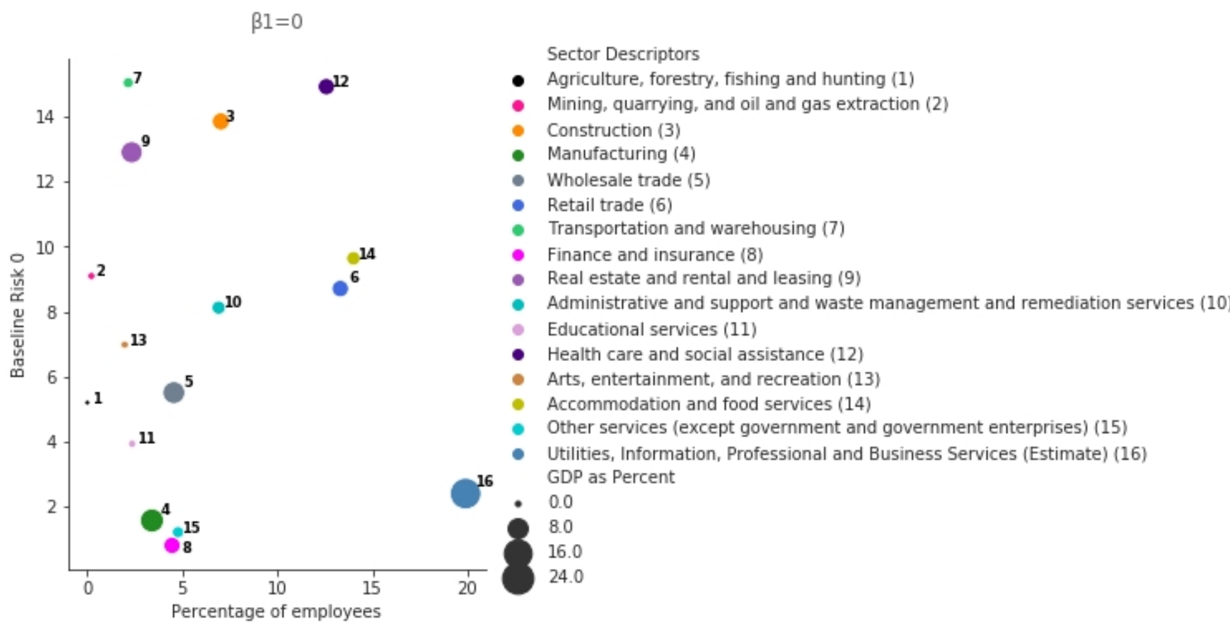


(a) Baseline Risk (cont'd.)

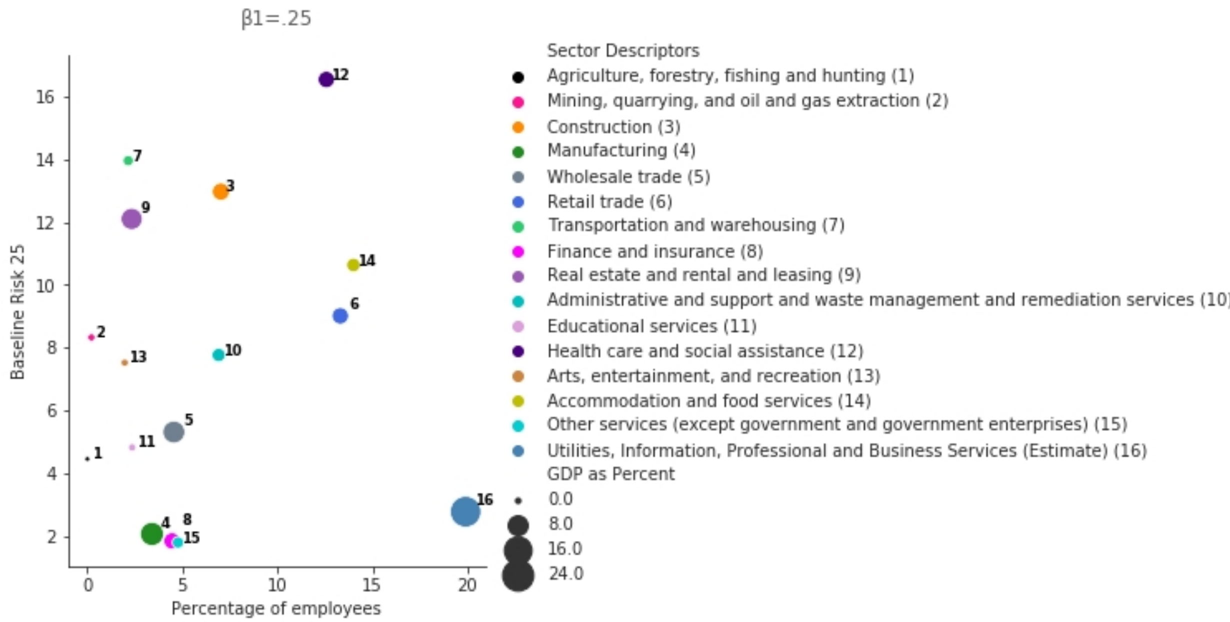


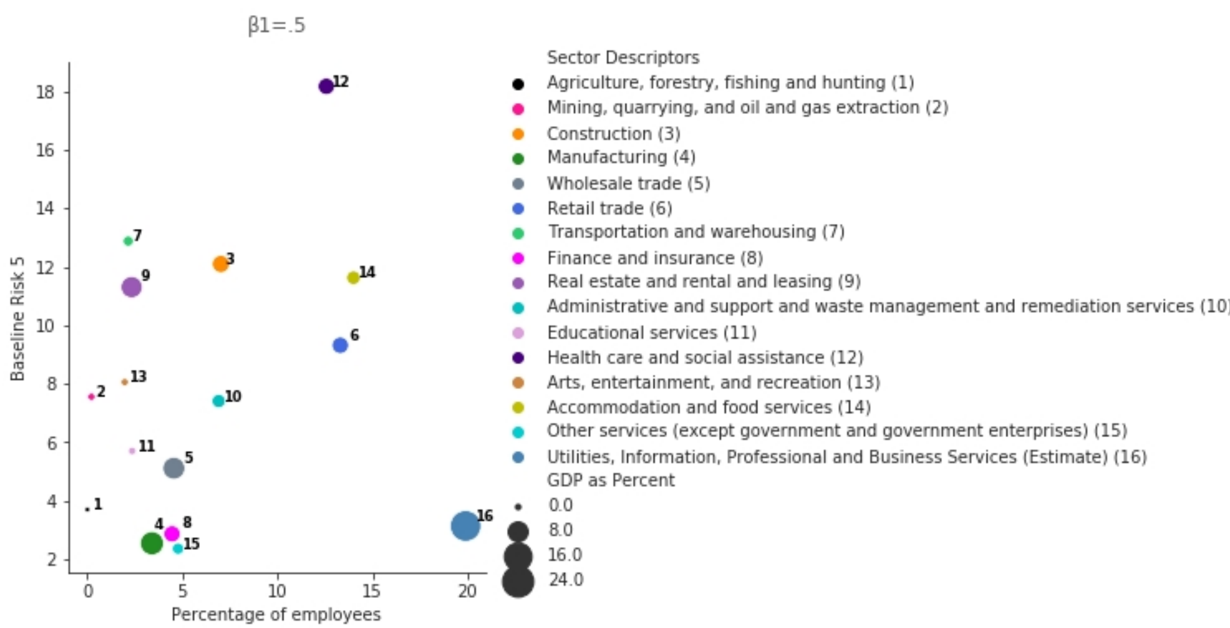
Source: Authors' calculations based on data from O*Net Survey (US Department of Labor 2019).

(b) Industry-Specific Policy Mitigation Tradeoffs

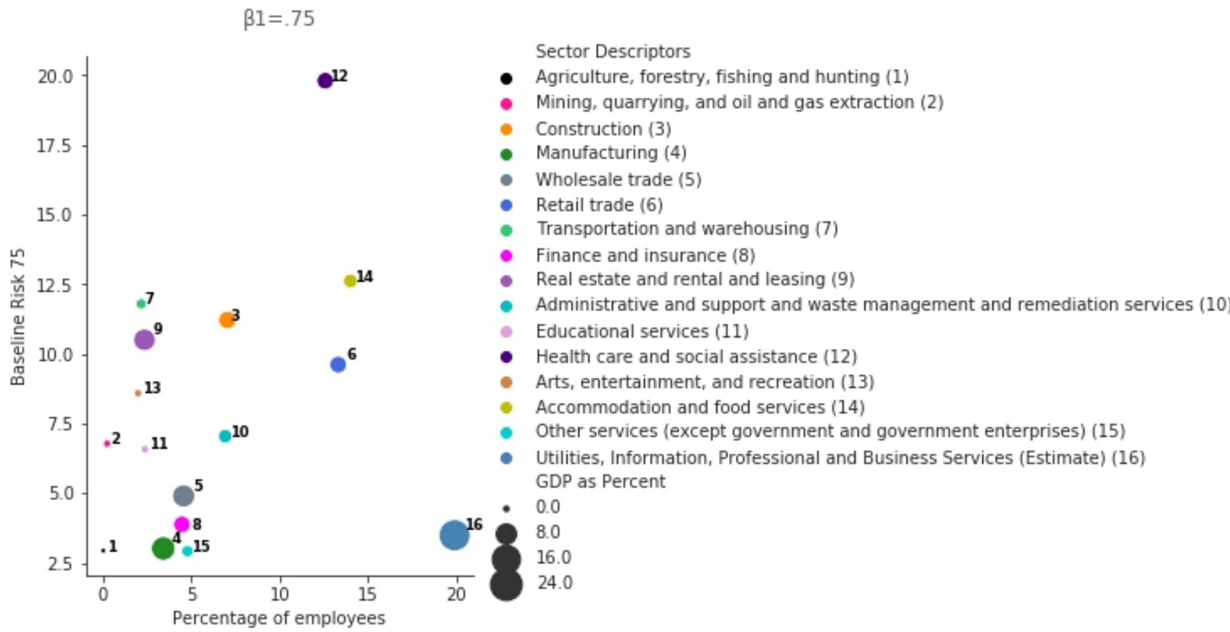


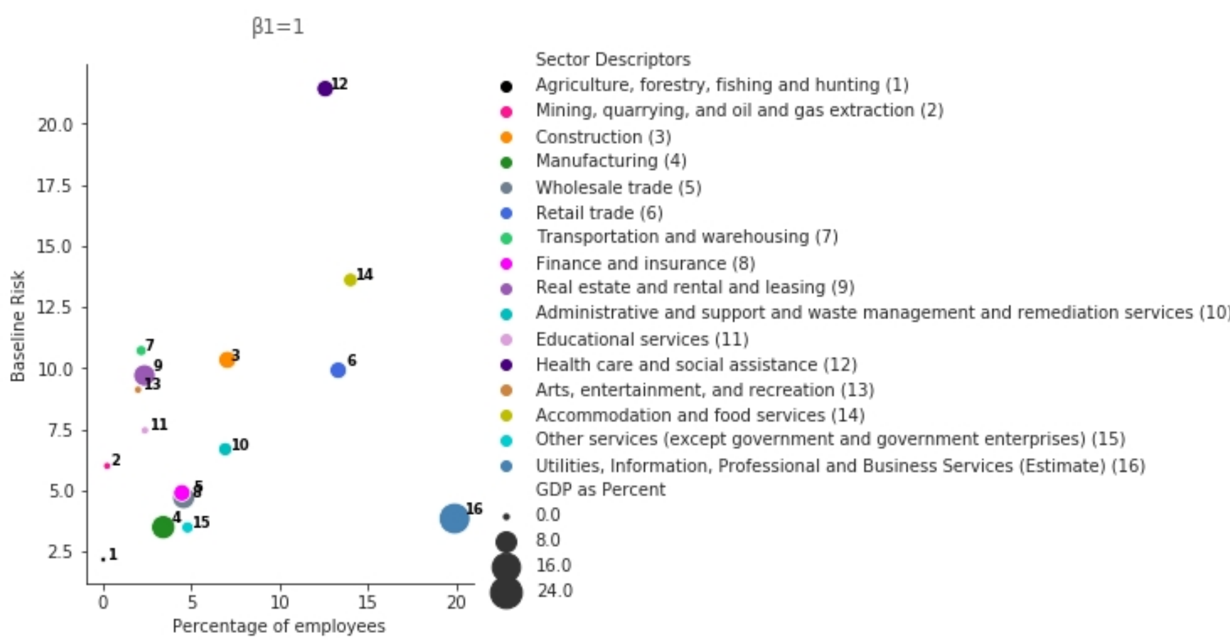
(b) Industry-Specific Policy Mitigation Tradeoffs (cont'd.)



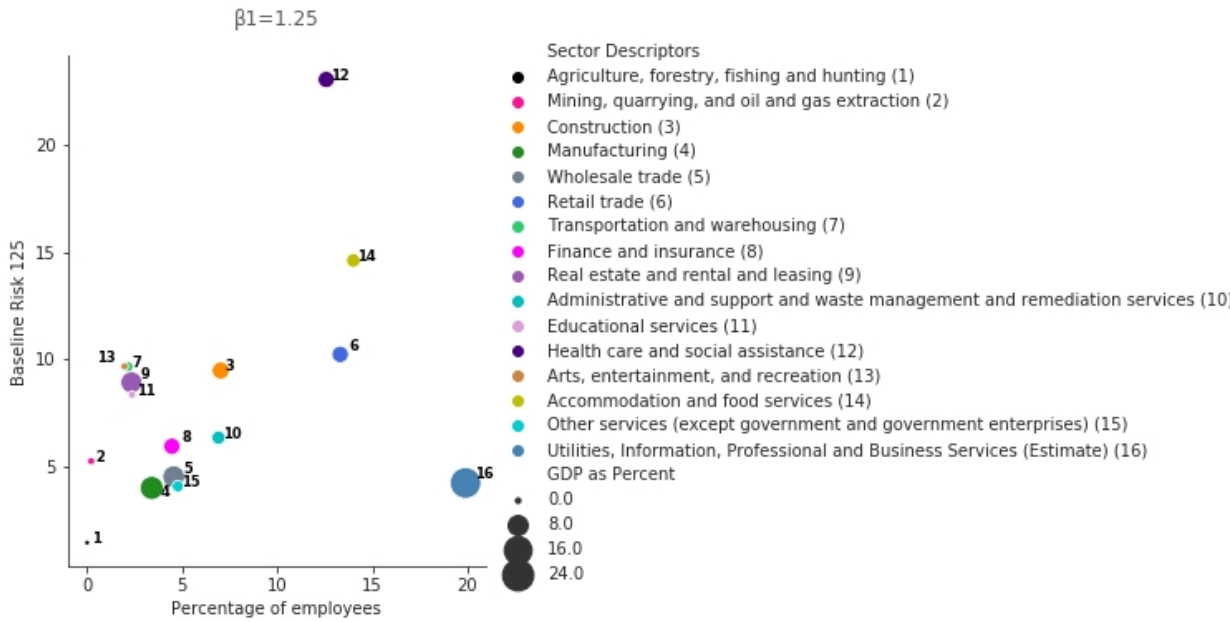


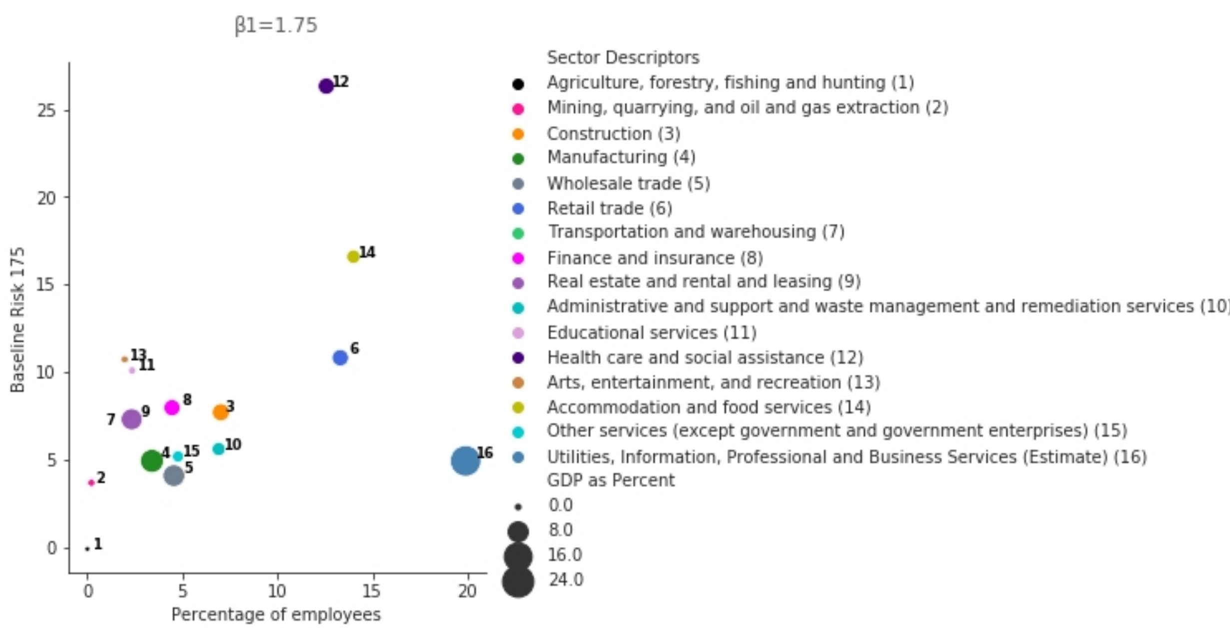
(b) Industry-Specific Policy Mitigation Tradeoffs (cont'd.)



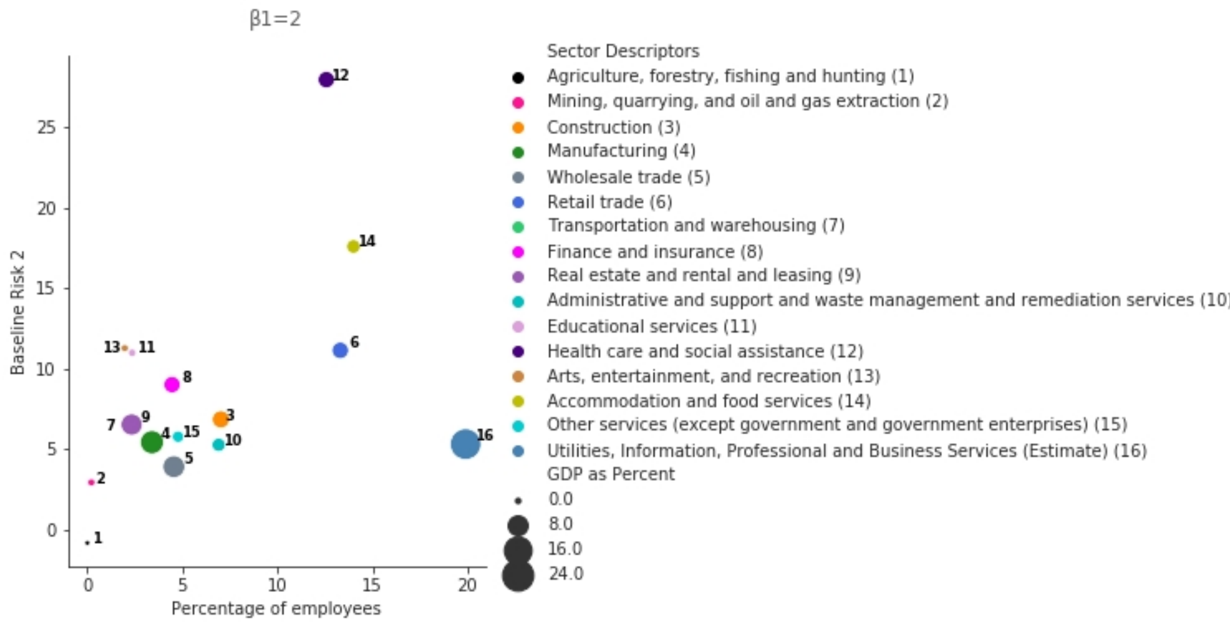


(b) Industry-Specific Policy Mitigation Tradeoffs (cont'd.)





(b) Industry-Specific Policy Mitigation Tradeoffs (cont'd.)



Source: Authors' calculations based on data from US Bureau of Economic Analysis (2020) and the O*Net Survey (US Department of Labor 2019).