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BACHELOR THESIS

Unemployment in the Czech Republic and Job Search on the Internet

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature.

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Prague, May 15, 2015

Signature

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Abstract

This thesis examines the relationship between Czech unemployment rate and job search related behavior of Internet users. The study uses a simple autoregressive model and augments it with search query data from two most popular Czech search engines, Google and Seznam, as well as data on numbers of job vacancies and reactions to them from job search portal Jobs.cz. Our results show that data on number of job vacancies can moderately improve short-term forecasts ("nowcasts") of Czech unemployment rate in terms of RMSE and MAE, whereas search query data from Google and Seznam failed to improve predictive ability of the baseline model.

Keywords unemployment rate, Czech Republic, Google Econometrics, search engine, job vacancies

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Abstrakt

Tato práce zkoumá vztah mezi českou mírou nezaměstnanosti a chováním uživatelů Internetu týkajícím se hledání práce. Studie používá jednoduchý autoregresní model, doplněný o data o vyhledávacích frázích ze dvou nejoblíbenějších českých internetových vyhledávačů, Googlu a Seznamu, a současně data o počtu nabízených pozic a reakcí na ně z portálu pro hledání práce Jobs.cz. Naše výsledky ukazují, že údaje o počtech nabízených pozic mohou mírně vylepšit krátkodobé předpovědi ("nowcasty") české míry nezaměstnanosti z hlediska RMSE a MAE, zatímco s daty o vyhledávacích frázích z Googlu a Seznamu nebylo dosaženo zlepšení předpovědí v porovnání se základním modelem.

Klíčová slova míra nezaměstnanosti, Česká republika, Google ekonometrie, internetový vyhledávač, volné pozice

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Acronyms

ADF	Augmented Dickey-Fuller
API	Application Programming Interface
AR	Moving Average
ARIMA	Autoregressive Integrated Moving Average
ARIMAX	Autoregressive Integrated Moving Average with Exogenous Inputs
ARMA	Autoregressive Moving Average
ARMAX	Autoregressive Moving Average with Exogenous Inputs
BMA	Bayesian Model Averaging
CSV	Comma Separated Values
CZSO	Czech Statistical Office
DM	Diebold-Mariano
GDP	Gross Domestic Product
GLS	Generalized Least Squares
GT	Google Trends
ILO	International Labour Organization
MA	Autoregressive
MAE	Mean Absolute Error
MSE	Mean Squared Error
PC	Principal Component
PCA	Principal Component Analysis
RMSE	Root Mean Squared Error
RUR	Range Unit Root
SEATS	Signal Extraction in ARIMA Time Series
TRAMO	Time series Regression with ARIMA noise, Missing values and Outliers

Master Thesis Proposal

Author	Ondřej Zacha
Supervisor	Petr Polák, MSc.
Proposed topic	Unemployment in the Czech Republic and Job Search on the Internet

Topic characteristics Macroeconomic indicators are usually obtained with a time lag, but policymakers need to obtain them as soon as possible. Nowadays, Internet users generate data that can serve as a source for predicting macroeconomic variables almost in real time. Search engines such as Google collect and publish data about volumes of search queries. Google Econometrics is a field of econometrics that uses these data for short-term predictions of macroeconomic variables. Unemployment has been a popular subject of study. One of the first papers was Google Econometrics and Unemployment Forecasting (Askitas & Zimmermann 2009). Similar approach has been applied to many countries, including the Czech Republic. In comparison with western countries, Czech search engine market is distinguished by extremely high share of Seznam.cz. In my thesis I will analyse historical data about search queries from Seznam.cz related to the job search and their usability for estimating rate of unemployment and check if these data provide results similar to previous studies or there is some difference.

Hypotheses 1. Internet search query data are a significant variable for estimating the rate of unemployment in the Czech Republic. 2. Seznam.cz outperforms Google Trends as a data source for unemployment predictions. 3. Web traffic on servers for job search is a significant variable for estimating the rate of unemployment in the Czech Republic.

Methodology I will use data about search query data from Seznam.cz (from the analyst department) and Google Trends (publicly available from www.google.com/trends) and about visits of servers for job search. These will be used in a regression model.

Outline

1. Introduction
2. Literature Review
3. Theoretical Concepts
4. Data and Empirical Model
5. Results
6. Conclusion

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Chapter 1

Introduction

Decision makers these days need reliable and up-to-date information as a foundation for their decisions, in order to be able to react promptly and accurately. In particular, macroeconomic indicators should be delivered in a timely manner. This has become even more important during the economic downturn, when adequate reaction was especially necessary to apply measures according to the situation. Nevertheless, many indicators such as GDP or unemployment rate are usually published with a significant delay, making the timely and adequate measures difficult to take.

In order to address this issue, economic researchers started to forecast the contemporaneous values, often using other additional variables that are published with smaller or no delay. This activity was later named "nowcasting". Similarly to meteorologists, who use this expression for short-term weather forecasts, economists use the term to describe "predictions of the present, very near future and very near past" (Banbura *et al.* 2010).

In 2008, Google launched Google Insights for Search, allowing anyone to explore and download data about development of popularity of different search queries from its Google Trends service. This provided researchers with a source of valuable data useful for various models and gave rise to a new field called Google Econometrics. In one of the most famous studies, Ginsberg *et al.* (2009) showed that Google Trends data can be used for tracking influenza-like illnesses. In the field of economics, e.g. Suhoy (2009) or Askitas & Zimmermann (2009) used these data for nowcasting of unemployment rate.

While most of the studies somewhat relied on the fact that Google is by far the most often used search engine in a majority of countries, this does not apply completely to the Czech Republic. A local search engine Seznam.cz holds a substantial share of the searches on the Czech internet. We have obtained data on a carefully selected set of search queries from Seznam.cz and downloaded the corresponding series from Google Trends. In addition, we work with the data on job vacancies and answers to them from one of the most popular Czech job search portals, Jobs.cz.

We use the obtained data to augment a simple autoregressive model of unemployment rate. We observe the changes of predictive ability of the models after adding extra variables to determine their usefulness for unemployment forecasting in the Czech Republic and also to compare the explanatory and predictive power of data from the rival search engines. The thesis is structured as follows. In Chapter 2 (Internet in the Czech Republic), we elaborate on the description of Czech internet environment, concentrating on job-search related issues. Chapter 3 (Literature Review) covers previously published studies on related topics. In Chapter 4 (Data), we describe the utilized data and their sources. Chapter 5 (Methodology) provides an overview of methods used in this thesis. Chapter 6 (Empirical Results) shows the final findings of our study. Chapter 7 (Discussion) mentions several limitations of our approach. In Chapter 8 (Conclusion), we summarize our results and also suggest ideas for further research.

Chapter 2

Internet in the Czech Republic

A study examining connection of development of job search on the Internet (or on Google, to be specific) and development of unemployment rate in a given country necessarily needs some conditions to be fulfilled. For instance, the share of people using the Internet or specific search engines has to be high enough for the sample to be representative. In this chapter, we describe particularities of Czech internet environment and its differences to situation in other countries.

One of the concerns is the amount of people that use the Internet for job search related activities or in general. Nowadays this may seem to be a minor issue; however, at the beginning of the observed time period, the situation was different. In 2008, the proportion of households with Internet access in the EU15 area was about 60 %, depending on the area—mentioned statistic distinguished three types of households according to the density of population of the area (Eurostat 2015a). As for the Czech Republic, the proportion was as low as 41 % for sparsely populated areas. Naturally, the percentages have risen over time and also values for Czech Republic converged to those of EU15, reaching percentages 74–85 and 77–85, respectively. The full comparison is available in Table B.1.

Apart from the lower usage of Internet in households, there is another important difference with western countries. Czech Republic is one of the countries where Google's services do not have an indisputably dominant position. Until about 2010, the majority of the web searches had been provided by Seznam.cz, a leading web portal and search engine in the Czech Republic (Internet Info 2010). The increase in Google's popularity in the past years is likely to be connected with its localization to Czech and expansion of smartphones and Google Chrome and Mozilla Firefox browsers, which used Google's search engine by default. According to TOPlist.cz[1], Google dominates Czech web search with 60 %, leaving 37 % to Seznam.cz. Complete development of search engine shares is presented in Table 2.1.

Table 2.1: Search engine shares in the Czech Republic

	2006	**2007**	**2007**	**2008**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Seznam	63%	63%	62%	63%	61%	60%	47%	44%	37%	37%	38%	37%
Google	24%	25%	29%	30%	33%	32%	48%	53%	53%	54%	58%	60%
	Source: NAVRCHOLU.cz						Source: Google Analytics				Source: TOPlist.cz	

Source: Internet Info (2009; 2010); Effectix.com (2014); TOPlist (2015)

Seznam.cz has been founded in 1996 and has gained substantial popularity among Czech Internet users since then (Sroka 1998). Besides a search engine, it runs a variety of services—an Internet version of yellow pages, most important in the early years, a free e-mail service, a news website and a map server. Variety and interconnectedness of the services, wide usage of free e-mail and popularity of Seznam.cz as a homepage for many internet users have all contributed to the high importance of Seznam.cz for Czech internet. As we wanted to investigate its role and impact, we use also search query data from Seznam.cz to explain development of Czech unemployment rate.

Vast majority of previously published studies concerning unemployment forecasting using data about behaviour of Internet users utilized Google's search query data, likely thanks to their easy availability. We wanted to supplement Google Trends as a predictor with data from another search engine because of the specific nature of Czech market. Apart from that, we are adding a different source of data describing internet behaviour of job-seekers—a job search portal Jobs.cz. This will allow us to include data about both supply and demand. Already one of the earliest studies by Ettredge *et al.* (2005) suggested using this kind of source for explaining unemployment. Nevertheless, to the best of our knowledge, no study utilizing job search portal data has been published yet.

The data from Jobs.cz help exploit the negative relationship between the unemployment rate and job vacancy rate, described by Beveridge (1944). During recessions, there are only few vacancies and high unemployment, during expansions, numbers of vacancies are high and unemployment is low. This relationship has become one of the most established stylized facts of macroeconomics, its dynamics is described by the Beveridge curve.

[1] Czech service for measuring web traffic

Chapter 3

Literature Review

After Google Trends and an interface for their exploration, Google Insights for Search, have been introduced in 2008, a number of works emerged that used search query data for estimating various phenomena, not only in economics. In fact, one of the first and most cited studies (Ginsberg *et al.* 2009) attempts to estimate weekly influenza activity in the US by analysing influenza-related Google search queries. Its impact led to launch of a specialized website Google Flu Trends[1] that attempts to predict influenza activity in various countries.

This field, eventually named Google Econometrics, quickly became popular. In the field of economics, it has been used for forecasting the housing market (Wu & Brynjolfsson 2009; Kulkarni *et al.* 2009; Hohenstatt *et al.* 2011), private consumption and customer sentiment (Della Penna & Huang 2009; Vosen & Schmidt 2011; Kholodilin *et al.* 2010), stock market moves (Preis *et al.* 2013) or portfolio risk (Krištoufek 2013), just to name a few.

To the best of our knowledge, as this is a fairly new research topic, there have been no publications that would address Google Econometrics in a more broad and comprehensive way. For the increasing usefulness and availability of the data at the same time, we can probably expect such work to be published soon.

The very first study that examined usability of web job search data for predicting unemployment did not use Google Trends, but WordTracker's Top 500 Keyword Report. It was conducted by Ettredge *et al.* (2005). The authors chose six keywords, tracked their daily search volumes and calculated short-term and long-term usage rates. On top of that, data about initial claims for unemployment benefits are used. Rather than a time-series model, several

[1] available at www.google.com/flutrends

single-variable regressions are utilized because of the limited availability of the data. The results showed a positive significant relationship between web search volumes of selected keywords and the number of unemployed in the US and suggested its usage for unemployment predictions.

Choi & Varian (2009b) present the power of Google Trends data for future research of "predicting the present". They use an example of models for retail, automotive and home sales and travel in various countries. The method utilized is a seasonal AR model, once supplemented by a fixed-effects model. Their results suggest a substantial improvement of forecast accuracy—up to 18% decrease in MAE.

Suhoy (2009) uses Israeli Google search query data from February 2004 to February 2009 for six categories: Human Resources (Recruitment and Staffing), Home Appliances, Travel, Real Estate, Food and Drink and Beauty and Personal Care. She examines usability of these indices as indicators of economic activity. In terms of job search related data, Suhoy works with the first mentioned category to predict unemployment rate and job openings ratio. The Human Resources category is reported to have the highest prediction power, according to the Granger causality tests.

Askitas & Zimmermann (2009) have studied usability of Google search query data for explaining monthly unemployment rate of Germany from January 2004 to April 2009. They examined Google activity for four groups of keywords: "unemployment office" or "unemployment agency", "unemployment rate", "personal consultant" or "personal consultancy", and a group of names of popular job search engines. For each group, they used data about Google activity in week 1 and week 2 and then in week 3 and week 4 of each month. They created several models using different combinations of keyword groups and time periods and compared them by means of Bayes Information Criterion. Their results show that Google search query data from week 3 and 4 of the previous month can work as predictors of current month unemployment rate.

Choi & Varian (2009a) used Google Trends data to predict initial claims for unemployment benefits in the US, a leading indicator of labour market. They work with a baseline AR(1) model of logarithmized initial claims and augment it with Google Trends time series for categories 'Jobs' and 'Welfare and Unemployment, using a time period from January 2004 to June 2009. The augmented model outperforms the baseline model in terms of out-of-sample MAE by 15.74 % and 12.90 % for a forecast using all data and for a forecast using only data since the recession, respectively.

D'Amuri (2009) used a similar approach for Italian unemployment rate. Since he only obtained quarterly data, he had to work with a smaller sample (2004:1 to 2009:1). Besides the Google search query index (here for the term "offerte di lavoro" / "job offers"), he uses an industrial production index and results of an employment expectations survey as explanatory variables. He compares 39 models that combine different explanatory variables and different sample sizes. He concludes that adding Google search query data to a model substantially increases its forecasting ability. For example, for a simple ARIMA(1,1,0) model, the MSE decreases by 33 % (for a greater sample) and by 50 % (for a shorter sample) when search query data are added.

D'Amuri then went on with US data. He and Marcucci (2010) conducted an exhaustive comparison of more than 500 models of US unemployment rate, augmented with Google Trends data for the keyword "jobs" and data on initial claims for unemployment benefits. Their primary interest lied in models that use first differences of US unemployment rate. As a robustness check, several other transformations have been used, as well as separate models at the state-level. Similarly to the previous papers, different time periods were available for different data sources—here 1967:1–2009:6 for unemployment rate and initial claims and 2004:1–2009:6 for Google Trends are used. Apart from simple AR(1) models augmented with Google Trends and initial claims data, other models with different lag structures are added to the comparison. Their findings support the usefulness of Google Trends data for unemployment forecasting in the US—augmented models significantly outperform the base ones. For the best model, the one-step-ahead forecast's MSE decreased by 29 % after adding GT data, for three-step-ahead the decrease was 40 %. In 2012, an updated version of this paper is presented (D'Amuri & Marcucci 2012). The same set of models is used, with a longer period used for computations. Also, even more robustness checks are performed. The results are very similar to the first version, Google Trends data are suggested to be used as a best leading indicator for predicting unemployment rate.

Bughin (2011) studies to which extent can Google Trends help nowcast unemployment claims and retail spending in Belgium using an Error Correction Model. He focuses solely on the explanatory power of Google Trends, rather than out-of-sample forecasts. In terms of unemployment claims, he utilizes the Phillips curve theory augmenting the baseline model also with data on Belgian inflation. He arrives at a conclusion that Google Trends data can serve for explaining macroeconomic fluctuations—a 10% change in search intensity is connected with a 0.4% change in unemployment claims.

As a first contribution from an emerging economy, Chadwick & Şengül (2012) present a similar approach based on data from Turkey from 2005:1 to 2011:12 in order to predict unemployment rate. They introduce Bayesian Model Averaging (BMA) to cope with model uncertainty—up to 20 keywords and up to 12 lags are used. Using the BMA procedure, 45 models are selected to be compared with the benchmark model, which only includes lags of the dependent variable. The results show that all models augmented with Google Trends data outperform the benchmark model in terms of RMSE for 1-, 2- and 3-step-ahead forecasts.

Fondeur & Karamé (2013) apply a similar technique to data on French youth unemployment (15- to 24-year olds). This age group is believed to be most likely to use Google for job search, which thereby minimizes the selection bias, noted by D'Amuri (2009). Because of the nature of the data (non-stationarity, multiple frequencies), an unobserved components approach is used. The forecasting results support the previous findings—Google Trends data can significantly improve unemployment rate predictions—with a 40% decrease of RMSE after utilizing Google Trends data.

Barreira, Godinho, & Melo (2013) present a comparative study from four European countries—Portugal, Spain, France and Italy. Apart from unemployment rate, car sales are also nowcasted. Again, they use Google Trends data for each country to augment the base models that use only lags of the dependent variable. To cope with the error caused by the sampling procedure used by Google, the Google Trends data are collected over a 14-day period and averaged afterwards, a technique used previously by Carrière-Swallow & Labbé (2013). Also, the data are seasonally adjusted by an ARIMA-X-12 procedure. The results are not as compelling as those presented in the above-mentioned studies. Google Trends data improved the predictions of unemployment rate only in three countries, in Spain, the prediction accuracy worsened after adding search query data. Regarding car sales, no consistent improvement of predictions accuracy has been achieved in any of the countries.

This corresponds with findings presented in Choi & Varian (2012). In this paper, they reemploy the methods from the previous version of the paper (Choi & Varian 2009b) in order to predict retail sales, travel, consumer confidence and, probably most importantly, initial claims for unemployment benefits in the US, as presented earlier in Choi & Varian (2009a). For those, they find an almost 6% increase in MAE after adding Google Trends data to the model. Authors point out that the Google Trends-augmented model performs well during the recession (until 2009), while the results have been less convincing since then.

Previously mentioned studies examined usefulness of data on job-related internet search for building unemployment models. The following studies do not fit perfectly in the described framework; however, they use some innovatory methods or focus on some minor, omitted but interesting issue.

Kholodilin, Podstawski, & Siliverstovs (2010) investigate usefulness of Google search query data for nowcasting of US private consumption. They employ an innovative method of transforming weekly Google Trends data to monthly series. Also, because multiple search queries are examined, principal components analysis is utilized to reduce dimensionality of the data.

Carrière-Swallow & Labbé (2013) use data on Google search queries to build nowcasting models for automobile sales in Chile. As Chile is a less developed country, not all features of Google Trends are available. They introduce a novel procedure of downloading the Google Trends series on 50 different days and average over that period to reduce the bias generated by Google's sampling method. In addition, they have to address the problem of missing search query categories. They construct an index using an auxiliary regression and also examine usefulness of principal components analysis.

Baker & Fradkin (2011) used Google Trends in their study of the relationship between length and intensity of job search and changes in duration of unemployment insurance in the US. They used daily data on search intensity of the keyword "jobs" for a proxy of job search duration.

Scott & Varian (2014) elaborated on the earlier works and developed an automated system of selecting predictors in a nowcasting model using structural time series models. They utilize some rather advanced techniques compared to the previously mentioned works, such as spike-and-slab regression or Markov chain Monte Carlo. These were used to model weekly initial claims for unemployment benefits and monthly retail sales.

As of now, there have been at least two studies concerning unemployment nowcasting in the Czech Republic. Platil (2014) examined the applicability of Google Econometrics in the Czech Republic. He uses Google search query data to model unemployment, consumer confidence, consumption and macroeconomic development. For the unemployment rate model, three different benchmark models have been used. These have been augmented with several explanatory variables—monthly share of unemployed, index of industrial production, confidence indicators, composite leading indicators and, most importantly, Google Trends data for five different keywords. The author thoroughly analyzes improvements in prediction error (MSE) after adding search query data. In addition, the process is repeated for three subsamples. The results show a statistically significant increase in forecasting accuracy in a vast majority of cases, with best achieved improvement of 10 %.

The other study (Pavlíček & Krištoufek 2015) focused straight on unemployment rate nowcasting, namely for Visegrad countries. They use the same methodology for each country, i.e. a set of three AR models with different lag structures augmented with Google Trends data for a query "job" translated to the respective languages. As for the results for the Czech Republic, Google Trends term turns out to be highly significant and strongly improve adjusted R^2 for all three models. All three models also outperform the benchmark models in terms of forecasting accuracy, for two models, the difference is statistically significant.

Chapter 4

Data

The data used for this thesis come from four different sources: the explained variable, unemployment rate, and Google Trends search query data have been obtained from publicly available sources, while search query data from Seznam.cz and data on job offers published on the job-search website Jobs.cz have been kindly provided by the analytical departments of the responsible companies. In this section, all used data sources are described.

4.1 Czech Statistical Office

Our objective is to track and to predict Czech unemployment. The Czech Statistical Office (CZSO) offers several indicators describing the Czech labour force: absolute numbers of employed and unemployed persons, employment rate, general unemployment rate, economic activity rate and share of unemployed persons. All series are seasonally adjusted and apply to those aged 15 to 64. For all of them, separate series for men and women are also available.

Data are collected by means of a Labour Force Survey using a randomly selected sample of households. The monitored indicators are in accordance with the definitions of the International Labour Organization (ILO) and Eurostat methodology (International Labour Organization 1982).

For our study, we selected the general unemployment rate. This indicator refers to the percentage of unemployed under the ILO standard within all economically active persons. According to ILO, *"the 'unemployed' comprise all persons above a specified age who during the reference period were:*

(a) 'without work', i.e. were not in paid employment or self-employment;

(b) 'currently available for work', i.e. were available for paid employment or self-employment during the reference period;

and (c) 'seeking work', i.e. had taken specific steps in a specified recent period to seek paid employment or self-employment. The specific steps may include registration at a public or private employment exchange; application to employers; checking at worksites, farms, factory gates, market or other assembly places; placing or answering newspaper advertisements; seeking assistance of friends or relatives; looking for land, building, machinery or equipment to establish own enterprise; arranging for financial resources; applying for permits and licences, etc."

Although some indicators are known earlier, general unemployment rate is published by the CZSO with a month delay at the end of the following month. The explained variable is monthly general unemployment rate of the aged 15 to 64 years. The series is seasonally adjusted using the TRAMO/SEATS method (for details, see Section 5.2). Data are available from 1993:01.

4.2 Google Trends

Data for the first explanatory variable come from Google Trends, a public web service for exploration of popularity of different search-terms on Google's search engine. Rather than absolute numbers or percentages of searches, Google constructs special indices. Although the data have been collected since 2004, Google Insights for Search, a service allowing anyone examine and download Google Trends statistics about any search query, have launched first in August 2008. Soon after the launch, many researchers started using the service for their studies, with Choi & Varian (2009b) or Ginsberg *et al.* (2009) being some significant examples. Later, in September 2012, Google Insights for Search have been merged into Google Trends.

For each search query, Google Trends analyse the development of its percentage within all searches for the same parameters, such as time period or country. Nevertheless, Google does not show the percentage directly, the figures are rescaled so that the highest percentage for a given time period is assigned with a value of 100. In addition to the separate search terms, Google Trends offer statistics also for the whole categories in selected regions. Similarly, a development of percentages of searches is captured, while the scaling is different—all categories start with a value zero at the beginning of a chosen period and percentage changes are reported. Google does not report statistics about all search queries—only those that pass a certain search volume threshold are described. The value of the threshold is not publicly known.

It is necessary to note that Google does not use the whole volume of searches for purposes of Google Trends analysis. As Carrière-Swallow & Labbé (2013) point out, a different sample is used every 24 hours and that can lead to additional noise. They built an API to collect data every day over a 50-day period and then used their average for the final estimation. A 5.8% standard deviation for the observed query "Chevrolet" was reported. Barreira *et al.* (2013) used a similar procedure, although only with a 14-day period, to reduce sampling noise for the terms "unemployment" in Portuguese, Spanish, French and Italian. They report average standard deviations from 3.5 % to 7.6 %.

Google Trends website has an intuitive interface for browsing search query statistics. For an example, see Figure A.2. Four attributes can be controlled: location, time period, category and type of search. Google allows to limit the statistics for a certain country or a smaller region (number of levels varies among countries) or to explore data worldwide. For the Czech Republic, state and region-level data are available.

As for the time period, the earliest data that Google reports come from January 2004. Users are allowed to choose any period from that point. For periods shorter than 90 days, daily data are reported, for longer periods, it is only weekly or monthly data, depending on the volume. There is no way of choosing frequency of the data. Except for three queries with lower search volumes ("práce jihlava", "práce ústí nad labem" and "práce karlovy vary"), we obtained weekly data. Since we needed monthly data for our purpose, a transformation had to be performed for the rest of the series. See Section 5.3 for details.

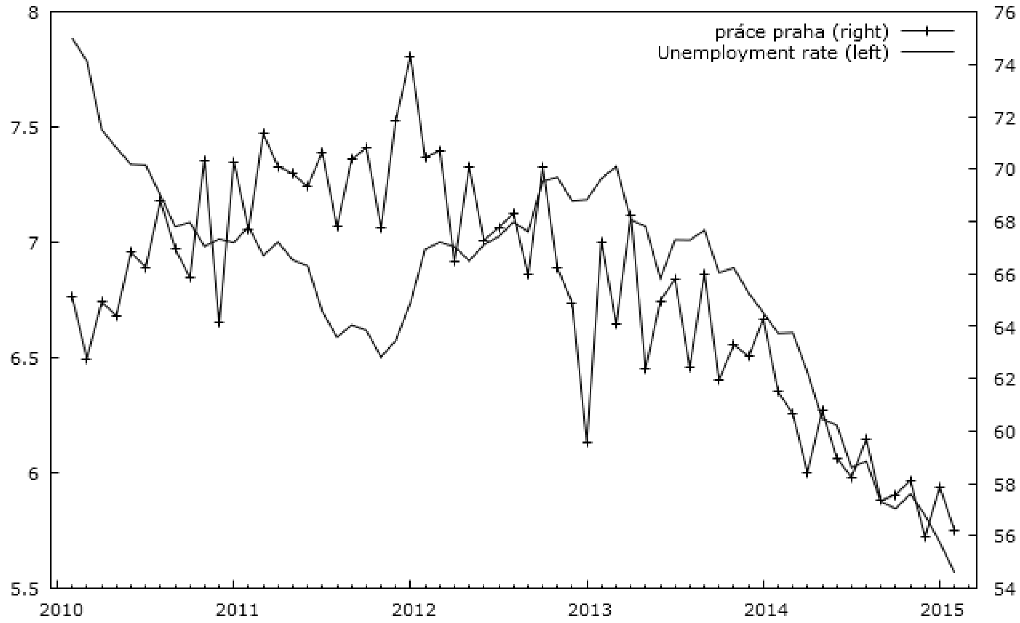
Searched queries are automatically sorted into categories for some regions. Users can use these to define their requested queries more precisely (compare e.g. search query "jobs" in a category "Jobs & Education" and in "Computer & Electronics"). In addition, these categories can be examined as a whole—and e.g. Choi & Varian (2009a) and Suhoy (2009) exploit this possibility. Unfortunately, categories are not available for the Czech Republic.

The last attribute is the type of search. Apart from Web Search, data for Image Search, News Search, Google Shopping and YouTube search results are available; however, we will only use the first one since it is the only relevant type for job-search purposes.

After setting the attributes, a time-series plot and a regional interest map is shown. Up to five queries can be described at the same time. Finally, the data set can be downloaded in a CSV format.

We obtained data on the set of search queries mentioned in the subsection 4.5, Choice of keywords. An example of Google Trends series (here for query "práce praha") is pictured in Figure 4.1.

Figure 4.1: Search index for query "práce praha" v. Czech unemployment rate



Source: Google, CZSO

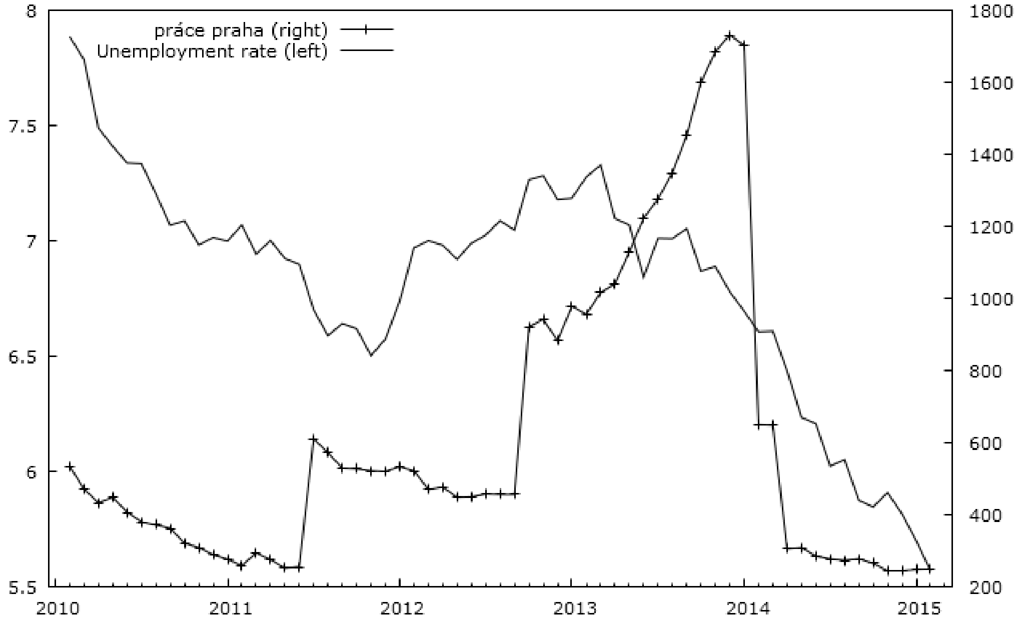
4.3 Seznam.cz

Seznam.cz does not have a specialized interface for downloading data about search queries. It does, however, provide publicly available "search statistics" for every query, although only for approximately last two months. Nevertheless, there is no overview of the most frequently used keywords as for Google Trends. Search statistics for each query can be accessed through a link at the bottom of a search results page. Nevertheless, these statistics are rather informative and there is no way of downloading the data directly in a spreadsheet or plain-text form.

As opposed to Google Trends, Seznam.cz reports the absolute search volumes. The data are presented in two ways—as a time-series plot and as statistics of minimum, maximum and average search volumes. For each query, exact matches are distinguished from extended matches (queries containing given keyword). An example of the search statistics page is provided in the Appendix: see Figure A.3.

Because of the limited public availability of the search statistics, complete data set has been obtained from the head of the analytical department of the company, Michal Buzek, after a previous e-mail correspondence. The data set contains absolute search volumes for each selected query from the set, using exact matches of queries. It covers time-period since 2010:02. An example of the series (again for query "práce praha") is pictured in Figure 4.2.

Figure 4.2: Search volumes for query "práce praha" v. Czech unemployment rate



Source: Seznam, CZSO

Many of the series exhibit a sudden drop at the beginning of 2014. This might be caused by the fact that Seznam's autocomplete function is being gradually improved and one of the updates might have affected search volumes heavily. As the data only cover exact matches of the search queries, the search volumes of some keywords could have decreased to the detriment of the newly suggested phrases.

In an attempt to account for this deviation, we obtained additional data on several "neutral queries" to check if the improvement of autocomplete function affected their volumes as well. We chose the following queries: “seznamka” (“dating site”), “youtube”, “email”, “facebook”, “google”, and three queries concerning adult content.[1]. Chosen queries are expected not to be subject to seasonal deviations or external influences—they should keep a roughly constant share among all queries. This characteristic was checked via a comparison with corresponding Google Trends series. Hypothetically, these series should show a similar decline due to improvements of the autocomplete function.

Surprisingly, these series (pictured in Figure A.1) show almost no long run development (but a strange deviation for one month, possibly an error). This indicates that the drop in the original data might be caused either by other external factors or by real decrease of demand for jobs.

4.4 Jobs.cz

The third source of data for explanatory variables differs from those usually used in the “Google Econometrics” studies. As Ettredge *et al.* (2005) suggested, we obtained data from one of the largest job search portals in the Czech Republic. Jobs.cz focuses mostly on highly specialized jobs and job seekers with tertiary education. These are not necessarily unemployed, usually they aim to switch jobs rather than find a completely new one. This subset of the job market can, however, still carry enough valuable information about the rest of the market.

Again, this data is not publicly available and has been obtained from the analytical department of the job search portal. The head of the department, Tomáš Dombrovský, has been contacted through e-mail and kindly provided the data set and also useful insight into company’s own utilization of gathered information at a personal meeting.

Two types of figures are reported. First, total amounts of job postings published on the portal in a given month. It is important to note that job postings might stay published for more than one month. A comparison with yearly numbers of job postings (not reported in this thesis) indicates that new job postings account on average for less than a half of the total monthly amounts. These are available from 2010:01. Second, monthly amounts of reactions to the job postings—these are available for a slightly shorter time period—from

[1] “porno”, “freevideo” and “redtube”

2011:05. Furthermore, a ratio of these two variables can be used as an additional variable.

The Figure 4.3 depicts the relationship between levels of unemployment rate and numbers of job vacancies and reactions to them. Please note that both series from Jobs.cz have been rescaled for the confidential nature of the data. Also, time-periods depicted vary according to availability of the data.

4.5 Choice of keywords

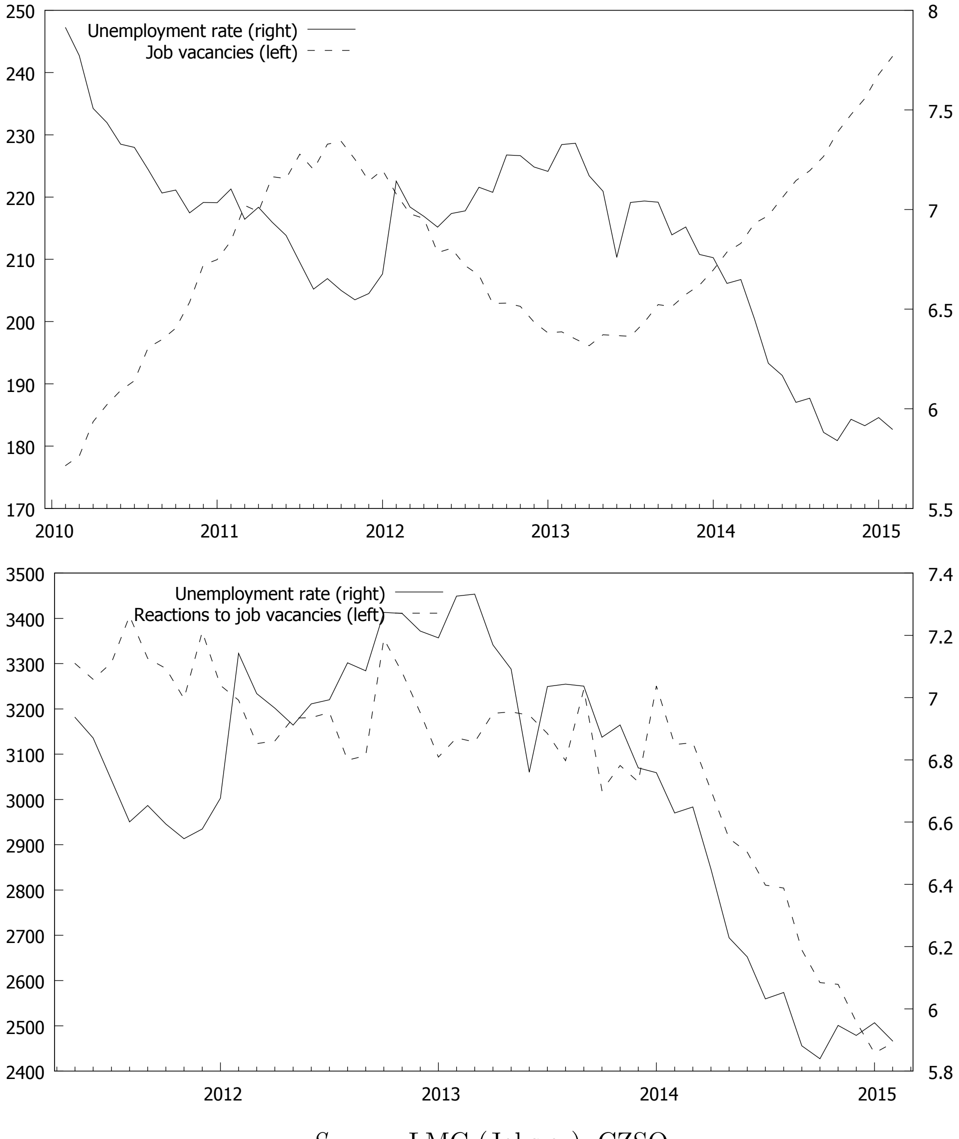
The selection of keywords is a key part of the study since it directly affects the explanatory power of search query data. It is important to capture the major ways of finding jobs used by job-seekers while bearing in mind possible increases of noise in the data.

In the previously published studies, there have been different approaches for the selection of queries. Since the vast majority used Google Trends, some of them made use of its categories, such as "Jobs" or "Welfare and Unemployment" (Choi & Varian 2009a; Suhoy 2009; Kholodilin *et al.* 2010; Bughin 2011; Vosen & Schmidt 2011). Some studies use just the keyword "job" or "jobs" or its equivalent in a given language, for instance D'Amuri (2009), Fondeur & Karamé (2013) or Pavlíček & Krištoufek (2015). Barreira *et al.* (2013) used translations of the word "unemployment". Others used multiple keywords and their combinations. Askitas & Zimmermann (2009) utilize four groups of keywords: "unemployment office OR unemployment agency", "unemployment rate", "personal consultant OR personal consultancy" and a group of most popular job search engines in Germany, taking advantage of Google's support of disjunctions of keywords. Chadwick & Şengül (2012) use a variety of terms—"looking for a job", "job announcements", "cv", "career", "unemployment" and "unemployment insurance". Similarly for the Czech environment, Platil (2014) uses a set of queries including terms "job", "employment", "job offers", "labour office" and "CV".

There is the same set of keywords used for both search engines, Google and Seznam. In order to select the keywords, we chose to conduct a survey among possible job-seekers. The survey had a form of an online questionnaire, utilizing the Google Docs platform.

Possible participants have been contacted through a number of most popular Facebook interest groups specialized for job search in Czech cities, such as

Figure 4.3: Unemployment rate, job vacancies (rescaled), reactions to job vacancies (rescaled)



Source: LMC (Jobs.cz), CZSO

"BRIGÁDY PRÁCE PRAHA"[2] ("jobs, part-time jobs Prague"). The participants have been self-selected. Although the whole survey has been conducted in Czech, I will only provide the English translations. The most important question was: "If you were to search for a new job using an internet search engine, which query would you use? Please name at least three." In addition, two auxiliary questions have been asked: "Have you ever used the Internet for a job search?" and "Which internet search engine do you use most often?". In the end, participants were asked to enter personal demographic data—age, sex and region. As a result, 213 unique answers have been collected. More detailed results of the survey can be found in Table B.2.

The most frequently mentioned query was "práce", by a wide margin. This word can be translated as "job", "work", "labour" or "employment"; another—although much less frequently used—meaning is "thesis". This draws attention to the possible noise in the data stemming from the ambiguity of the meaning; however, we believe this affects our results only to an acceptable extent. Other answers included queries such as "nabídka práce" ("job offer"), "brigáda" ("temporary job"), "volná místa" and "volná pracovní místa" ("vacancies"). Respondents also frequently used the query "práce" together with a name of a city, so we included queries containing names of all county towns in the Czech Republic.

Search engine users can use queries with or without diacritics and thereby generate slightly different series. We decided to use only search queries with diacritics to keep the models simple. Also Seznam.cz seems to merge these queries for the purpose of creating search statistics, the reported figures for queries with and without diacritics are identical. The full list of keywords is as follows: "práce", "práce praha", "práce české budějovice", "práce plzeň", "práce karlovy vary", "práce ústí nad labem", "práce liberec", "práce hradec králové", "práce jihlava", "práce brno", "práce olomouc", "práce ostrava", "práce zlín", "brigáda", "volná místa", "volná pracovní místa" and "nabídka práce".

[2] available at www.facebook.com/groups/203900279809525/

Chapter 5

Methodology

This utilizes a standard framework commonly used for dealing with macroeconomic time-series. In this chapter, we present the methods used for estimation of the models as well as the preceding processes.

5.1 ARMA/ARIMA/ARMAX

ARMA (autoregressive–moving-average) model is a time series model for description of weakly stationary stochastic processes. A general ARMA model of order (p, q) has a form:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \quad (5.1)$$

With p and $q \in \mathbb{N}$ being orders of the lag polynomials, Y_t explained variable, Y_{t-i} lagged values of the explained variable and ϕ_i their corresponding coefficients; ε_t white noise (a process with no serial correlation, zero mean and time invariant finite variance) ε_{t-i} its lagged values and θ_i their corresponding coefficients.

It can be decomposed into two parts: AR(p) (autoregressive) and MA(q) (moving average). Both can be understood as special cases of the ARMA(p, q) model.

A general Moving Average (AR) model of order p has a form:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_t \quad (5.2)$$

A general Autoregressive (MA) model of order q has a form:

$$Y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \quad (5.3)$$

When stationarity condition is not met, a generalization of an ARMA model can be used in some cases: an Autoregressive Integrated Moving Average (ARIMA) model. In comparison with the ARMA model, it is extended by an integrated part I(d), where d stands for the order of integration, and thereby allows to handle non-stationary series.

In this thesis, we will use only a simple AR(1) process for the baseline model to retain parsimony; our choice is based on the fact that the same model is used in the majority of previous studies (e.g. Choi & Varian 2009a; D'Amuri & Marcucci 2010; Kholodilin *et al.* 2010), together with the its seasonal version (Choi & Varian 2009b; Askitas & Zimmermann 2009) and on a series of pretests that compared models using information criteria.

An AR(1) process has a form:

$$Y_t = c + \phi_1 Y_{t-1} + \varepsilon_t \tag{5.4}$$

Similarly to the cross-sectional or panel data estimation methods, additional explanatory variables can be added to the ARMA/ARIMA model to form an autoregressive (integrated) moving-average model with exogenous inputs (ARMAX/ARIMAX). This will allow us to explain the development of unemployment rate not just with its historical values but also with additional information, namely data about internet behavior of job-seekers. The resulting model has a form:

$$\begin{aligned} Y_t = c + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_b x_b \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + +\phi_p Y_{t-p} + \\ + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \end{aligned} \tag{5.5}$$

Statistical software package Gretl is used for the estimation.

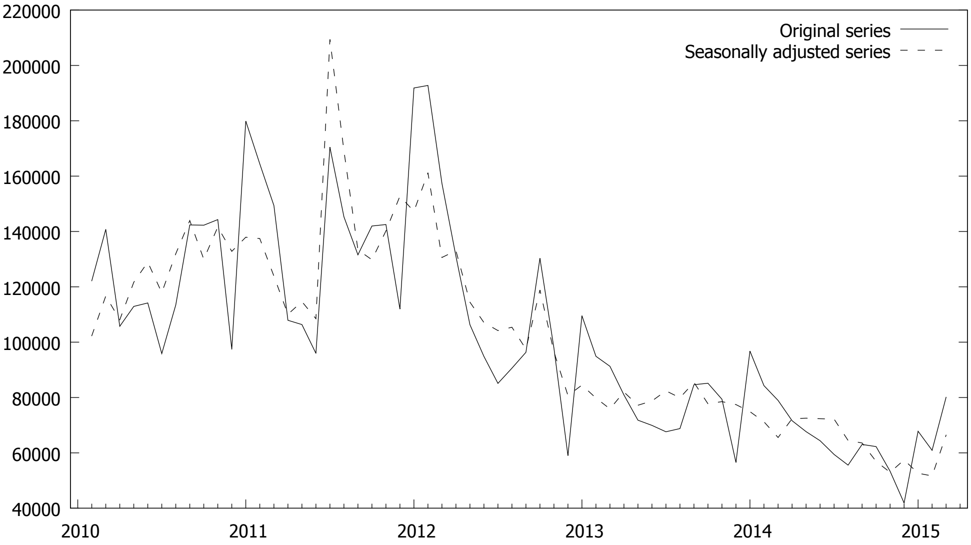
5.2 Seasonal adjustment

Unemployment-related time series provided by the CZSO are seasonally adjusted in order to remove seasonal calendar effects. Unemployment rate time series typically show a strong seasonality—e.g. regular strong increases at the beginning of a year or low levels in summer. Seasonal adjustment allows then for observing long term trends.

In order to maintain consistency in the data set, we performed the same adjustment procedure on the explanatory variables.

The procedure utilizes the TRAMO/SEATS method developed by Gómez &

Figure 5.1: Example of seasonally adjusted series: query “práce” from Seznam.cz



Maravall (1996) of Bank of Spain. It consists of two programs TRAMO (“Time Series regression with ARIMA Noise, Missing Observations and Outliers”) and SEATS (“Signal Extraction in ARIMA Time Series”). The former performs pre-adjustment and removes deterministic effects, the latter decomposes the time series into components.

This method is commonly used by European public organizations thanks to the official support of Eurostat. It has been also used e.g. in D’Amuri & Marcucci (2012) or Platil (2014). The program has been implemented in JDemetra+, a software package developed right for Eurostat and officially recommended for seasonal adjustment of official statistics (Eurostat 2015b)

Other methods of coping with seasonalities in the data include X-12-ARIMA or its successor X-13ARIMA-SEATS, both developed by United States Census Bureau (Bureau 2015), used e.g. by Barreira *et al.* (2013); using year-on-year growth rates (Carrière-Swallow & Labbé 2013; Chadwick & Şengül 2012), or a seasonal AR model with a 12 month lag (Choi & Varian 2009a; Askitas & Zimmermann 2009).

An example of series seasonally adjusted by TRAMO/SEATS method can be seen in Figure 5.1.

5.3 Transformation of Google Trends data

Since most of the series obtained from Google Trends had weekly frequency, we had to convert the series to monthly observations to match with the rest of the series. As noted earlier, some of the series were already downloaded with a monthly frequency. While e.g. Askitas & Zimmermann (2009) choose to use transformed biweekly series, Bughin (2011) or Chadwick & Şengül (2012) average the weekly observations, we chose an approach already used in Kholodilin *et al.* (2010).

Because of the presence of overlapping weeks, a simple averaging method is not sufficient. First, weekly data are interpolated to daily frequency. As a next step, daily figures within each month are aggregated and an arithmetical mean is computed. After this transformation, the maxima of the series will not be 100 as in the original series; however, this should not play a role for our estimation.

5.4 Stationarity

ARIMA-type models, utilized in this thesis, work with the assumption of stationarity. Series have to be stationary for the estimation to be correct. Two types of stationarity are defined. According to Tsay (2005), *"a time series $\{r_t\}$ is said to be strictly stationary if the joint distribution of $(r_{t_1}, \ldots, r_{t_k})$ is identical to that of $(r_{t_1+t}, \ldots, r_{t_k+t})$ for all t, where k is an arbitrary positive integer and $(t_1, \ldots, t_k)$ is a collection of k positive integers."* This condition is difficult to verify and also very rarely encountered when working with real economic data. Hence, a weaker version of stationarity is often used. *"A time series $\{r_t\}$ is weakly stationary if both the mean of r_t and the covariance between r_t and r_{t-l} are time-invariant, where l is an arbitrary integer"* (Tsay 2005). In other words, a series is weakly (covariance) stationary if it has a constant mean and time-invariant finite covariances.

Stationarity of an ARMA(p, q) process depends on its AR part; an MA process is always stationary. An ARMA(p, q) process (5.1) is weakly stationary if the roots to z of

$$1 - \phi_1 z - \phi_2 z^2 - \ldots - \phi_p y^p = 0 \tag{5.6}$$

are all in modulus larger than 1 ($|z| > 1$). In other words, if the above-mentioned polynomial has a unit root, it is classified as non-stationary.

If a series is found non-stationary, then it should be differenced (possibly multiple times) until stationarity is achieved, according to the Box-Jenkins methodology (Box & Pierce 1970). A process with one unit root is called integrated of order one, I(1). Similarly, a process with d unit roots is called integrated of order d, I(d). Such process can be made stationary by taking d differences.

Macroeconomic series (such as unemployment rate) are often subject to trends and stationarity is really hard to justify. On the other hand, as Montgomery *et al.* (1998) or Koop & Potter (1999) point out, unemployment rate, bounded within the unit interval, should not show signs of presence of a unit root. Similar limitations apply to the Google Trends series, but not Seznam or Jobs.cz series; unit root tests thus have to be conducted in any case.

There are several stationarity tests that seek for the presence of a unit root. The probably most popular one is Augmented Dickey-Fuller test, used also e.g. by Suhoy (2009) or Barreira *et al.* (2013), or Kwiatkowski-Phillips-Schmidt-Shin. They are usually quite sensitive and often easily tend to mark series as non-stationary (Choi & Moh 2007). D'Amuri & Marcucci (2010) utilize a modified version the Augmented Dickey-Fuller test, ADF-GLS or a Range Unit Root (RUR) test to fit better to the characteristics of used series.

5.5 Augmented Dickey-Fuller Test

In this thesis, we will use the Augmented Dickey-Fuller test to examine stationarity of the series. The ADF test is based on an OLS regression

$$\Delta Y_t = (c) + (dt) + \alpha Y_{t-1} + \zeta_1 \Delta Y_{t-1} + \zeta_2 Y_{t-2} + \ldots + \zeta_{p-1} Y_{t-p+1} + \varepsilon_t, \quad (5.7)$$

– depending if we consider a constant c and/or a time trend d in the model or not. ADF test uses a modified t-distribution—Dickey-Fuller distribution. The ADF statistic is a negative number, lower numbers meaning stronger rejection of the H_0 hypothesis:

H_0: $\alpha = 0 \Leftrightarrow$ *'the series has a unit root'*.

H_1: $\alpha \leq 0 \Leftrightarrow$ *'the series is stationary'*.

5.6 Principal Component Analysis

Many of the previous studies used search query data just for one employment-related keyword, as noted earlier. In our thesis, we want to capture job-seekers' web search behaviour in a more complex manner, using data from Google Trends and Seznam.cz. Since Google Trends statistics for the whole categories are not available for the Czech Republic and there are no similar categories for the Seznam data, we decided to use multiple search queries based on a previously conducted survey.

Our data set contains time series for 18 search queries from each search engine. One of the possibilities would be to use each of them as a separate variable. In order to keep the collected information from one search engine in one model and retain a reasonable number of models, we had to "compress" the information contained in the data set. This approach also increases degrees of freedom for the estimation compared to the case of using all variables in one model.

A similar issue has been already addressed earlier in previous studies. Carrière-Swallow & Labbé (2013) use an auxiliary model to estimate weights used for construction of a new Google Trends index. A more frequently used technique (Kholodilin *et al.* 2010; Vosen & Schmidt 2011; Carrière-Swallow & Labbé 2013; D'Amuri & Marcucci 2012) makes use of principal component analysis and has been described by Stock & Watson (2002).

Principal Component Analysis (PCA) is a statistical procedure introduced by Pearson (1901). It transforms a set of original variables into a new set of linearly uncorrelated variables—principal components. These have an orthogonal structure and are designed to preserve all variance in the data. The first generated variable—first principal component—accounts for as much variance as possible, each next component explains as much of the remaining variance as possible while complying with the condition of uncorrelatedness.

5.7 Forecasting and its evaluation

In this thesis, a comparison of forecasting ability of our models is of greatest interest. Similarly, most studies from the Google Econometrics field aim to "nowcast" various economic indicators, having this as a primary goal, rather than focusing on significance of variables and formal model quality statistics.

Since nowcasting aims for contemporary values, we only work with static one-step-ahead out-of-sample forecasts. The full sample is divided into two subsamples—the first one is used for estimation, the second one for forecast evaluation. Since we forecast values that are already known, this method is sometimes called "pseudo out-of-sample". We choose the last 12 months (March 2013 to February 2015) as "test data" for nowcasting, while estimating the models on the first 49 months of the selected period (February 2010 to February 2014).

5.7.1 Evaluation

In order to evaluate the predictive ability of the models, we use Root Mean Squared Error and Mean Absolute Error. These metrics have been frequently used in the previous studies, we will thus be able to compare the gains of predictive ability of our models easily. Moreover, Diebold-Mariano test is utilized to find statistically significant differences within our set of models.

Each technique operates with the prediction error. It is defined as difference between the actual values and the predictions:

$$e_{t+h|t} = Y_{t+h} - \widehat{Y}_{t+h|t} \tag{5.8}$$

5.7.2 Mean Absolute Error (MAE)

Mean Absolute Error is defined as an average of absolute values of the prediction error over the forecasted period.

$$MAE = \frac{1}{T}\sum_{t=1}^{T} |e_{t+h|t}| \tag{5.9}$$

5.7.3 Root Mean Squared Error (RMSE)

Root Mean Squared Error is defined as a square root of the average of squared prediction errors over the forecasted period.

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(e_{t+h|t})^2} \tag{5.10}$$

5.7.4 Diebold-Mariano (DM) Test

Diebold-Mariano test (Diebold & Mariano 1995) serves to compare accuracy of two competing forecasts. When comparing a set of forecasts, one is usually chosen as a benchmark. First, a loss differential d_t between model A and B is defined:

$$d_t = L\left(e^A_{t+h|t}\right) - L\left(e^B_{t+h|t}\right), t = 1, \ldots, T, \tag{5.11}$$

where $e^A_{t+h|t}$ and $e^B_{t+h|t}$ denote prediction errors made by h-step-ahead forecasts from model A and B, respectively and L denotes a selected loss-function, e.g. $L(x) = |x|$ or $L(x) = x^2$. The null hypothesis is then defined as follows.

$$H_0 : E[d_t] = 0 \Leftrightarrow E\left[L\left(e^A_{t+h|t}\right)\right] = E\left[L\left(e^B_{t+h|t}\right)\right] \tag{5.12}$$

$$H_1 : E[d_t] \neq 0 \Leftrightarrow E\left[L\left(e^A_{t+h|t}\right)\right] \neq E\left[L\left(e^B_{t+h|t}\right)\right] \tag{5.13}$$

In other words, the null hypothesis states that there are no quantitative differences between the forecasts of the two models A and B.

Chapter 6

Empirical Results

In this section, we present the results of our analysis of explanatory and forecasting power of web job search data. We conduct tests for stationarity, perform principal component analysis and finally make in-sample and out-of-sample performance comparison.

6.1 Stationarity

We examine stationarity of our data using an Augmented Dickey-Fuller unit-root test. We utilize Gretl's functionality for adjusting the maximum lag order by means of Akaike Information Criterion, with the highest lag set to 10 according to the recommendation by Schwert (1989).

Majority of the series shows signs of non-stationarity, with the exception of a few search query series, mostly from Seznam.cz. In order to get rid of stationarity, we take first differences of each series. For all of the new series, we reject the null of presence of unit-root even at 99% level, except for two Google variables ("práce liberec", "práce pardubice"). For these we take also second differences to examine the order of integration.

The results, reported in table 6.1, indicate that most of the series in dataset are integrated of order 1, two series show order of integration 2 and 12 series are stationary. Since we want to keep the models interpretable, we will continue to work with first difference series.

6.2 Principal Component Analysis (PCA)

In the next step, principal component analysis of two 18-item sets of variables—those from Google and from Seznam.cz—is carried out. Tables of both sets of principal components and the respective percentages of explained variance are reported below (Tables 6.2 and 6.3); additional details in Table B.3.

Both sets of PCs show a high concentration of variance in the first PCs—first three PCs for Google and Seznam data account for 72 % and 80 %, first ten account for 95 % and 97 % of variance, respectively. For the newly generated PCs, ADF tests are conducted. The series again show signs of non-stationarity in most cases. Taking first differences removes stationarity for all but the third and fourth PCs for Seznam data. For these series, second differences are generated—and according to the ADF test, the new series are stationary. See Table B.4 for complete results.

6.3 Model performance

Our goal is to compare the explanatory and predictive (nowcasting) power of web search query data from Google and Seznam and also examine the usability of data from the job portal Jobs.cz. We will describe the results in three subsections. In the first subsection, we will compare the predictive power of each individual query from both Google and Seznam. In the second subsection, we will compare aggregate models for data from both search engines to compare their usefulness as a whole. Lastly, we will inspect the Jobs.cz data and a set of models utilizing them. In each subsection, we will inspect both in-sample and out-of-sample performance of the models, using a few different measures.

In-sample performance is described by Adjusted R^2 ($\bar{R}^2$), computed manually as a squared correlation between fitted and original series, Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). For the comparison out-of-sample performance, RMSEs and MAEs are computed. The best performing models are then also tested for significant differences in forecast accuracy by means of a Diebold Mariano test.

First, we estimate our baseline model, which will be later used in all subsections. We use an AR(1) model for differenced unemployment rate, estimated using exact maximum likelihood method. All models are estimated using the time period from February 2010 to February 2015.

The regression results for the baseline model are reported in the Figure 6.1.

Figure 6.1: Baseline model estimation results

Model 1: ARMA, using observations 2010:02–2014:02 ($T = 49$)
Dependent variable: d_unempSA1
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value
ϕ_1	0.120364	0.141550	0.8503	0.3951

Mean dependent var	−0.024997	S.D. dependent var	0.111730
Mean of innovations	−0.022207	S.D. of innovations	0.112530
Log-likelihood	37.50689	Akaike criterion	−71.01378
Schwarz criterion	−67.23014	Hannan–Quinn	−69.57827

			Real	Imaginary	Modulus	Frequency
AR						
	Root	1	8.3081	0.0000	8.3081	0.0000

6.3.1 Models with individual variable performance

The baseline model is now augmented with the search query variables, one by one. We build 36 models, one for each variable. The in-sample results (reported in table 6.4) are somewhat ambiguous. All models are affected by the short length of the available sample and the models have a rather poor fit. For most of them, $\bar{R}^2$ has even negative values.

From the set of Google variables, only five increase the fit of the model: “práce praha”, “práce ústí nad labem”, “práce ostrava”, “volná pracovní místa” and “nabídka práce”. The last mentioned variable increased the fit by more than 1300 %. Together with “volná pracovní místa” are these the only variables that decrease the in-sample error.

Seznam variables show a similar performance, with only four variables improving the $\bar{R}^2$—“práce české budějovice”, “práce liberec”, “práce jihlava” and “práce olomouc”. None of the Seznam variables decreases the in-sample error.

Out-of-sample performance (described in Table 6.5) is rather poor, none of the variables improves the nowcasts. The nowcast accuracy worsens after adding any individual variable. There are no substantial differences between performances of models with Google and Seznam variables. The RMSEs increases range from 9 to 22 %, MAEs worsen by 6 to 20 %.

6.3.2 Models with multiple or aggregate variables

In this subsection, we compare the models that aggregate all information from each search engine, in order to evaluate and compare collective power of all search queries. The results are presented in tables 6.6 and 6.7. First, we incorporate all 18 variables from each search engine (denoted G ALL and S ALL for Google and Seznam, respectively). Second, since data from Seznam.cz are not indices but absolute numbers, it is meaningful generate a new variable "s sum"—a simple horizontal sum of all Seznam variables. Third, we make use of principal components. We use up to 18 (i.e. all) PCs for each search engine. The number in parentheses denotes the last principal component—e.g. "sPC (5)" stands for a model that includes first five principal components for Seznam data.

Adding all Google and all Seznam variables increases the in-sample fit substantially, with $\bar{R}^2$ increasing up to 0.30 and 0.36, respectively. While adding complete set of Seznam variables improves the $\bar{R}^2$ slightly more than adding corresponding Google variables, the latter reduce the in-sample RMSE and MAE more substantially.

Seznam data surprisingly do not add any explanatory power to the model, as measured by the $\bar{R}^2$ and in-sample errors, similarly to the individual variables described in the previous subsection.

In a comparison of PC performance, those for Google data seem to explain the dependent variable better, showing an $\bar{R}^2$ increase to 0.13 already for first two PCs. That indicates a good potential for further usage for modeling and forecasting purposes since these two PCs cumulatively account for more than 64 % of variance in the Google data set (see Table 6.2). On the contrary, Seznam's PCs show even negative $\bar{R}^2$ values for models with up to 15 PCs. Given the distribution of variance among PCs (see Table 6.3), Seznam's PCs show rather poor potential for further usage.

Nevertheless, most of these models suffer from overfitting the training data, which is often encountered when too many variables are included in the model. While the in-sample performance looks promising, the out-of-sample performance is poor. The nowcast accuracy worsens by 5 to more than 300 % in terms of RMSE and by 3 to almost 250 % in terms of MAE.

6.3.3 Models with job search portal data

Lastly, we want to assess the nowcast ability of Jobs.cz data on job vacancies and reactions to them. We focus mainly on the number of job vacancies published, but we also examine the reactions. The tables summarizing performance of the models are presented below (table 6.8 and 6.9). JV stands for job vacancies, JR for reactions. The number in parentheses denotes the highest included lag order of the JV variable.

Job vacancies improve the in-sample fit substantially at various lag order levels. A model incorporating this variable up to the third lag shows $\bar{R}^2$ 0.1, more than 16 times greater than the baseline model. On the contrary, reactions to job vacancies seem to have rather poor fit, getting negative $\bar{R}^2$ values.

Regarding out-of-sample performance, job vacancies seem to be the only variable improving the nowcast performance, according to our computations. Models augmented with job vacancies series up to the second lag to the model decreases RMSE by approx. 2 %. MAE decreases even in more cases, for models with maximum lag orders up to 6 and also 11 and 12, 7.6 % being the greatest improvement. The second variable, reactions to job vacancies, increases the prediction errors by more than 8 %.

6.4 DM test

For the forecasts that outperform the baseline model, we conduct the Diebold Mariano test to determine whether the difference in forecasting performance is statistically significant. The results are presented in a table 6.10.

We cannot reject the null hypothesis of identical forecast performance even at 10% level, the improvement of forecast accuracy is thus statistically insignificant.

Table 6.1: ADF test results for original variables: p-values

	Level	**First difference**	**Second difference**
unemp	0.81	<0.01	-
j_vacancies	1.00	<0.01	-
j_reactions	0.87	<0.01	-
g_p	0.65	<0.01	-
g_p_praha	<0.01	-	-
g_p_ceskebudejovice	0.91	<0.01	-
g_p_plzen	0.39	<0.01	-
g_p_karlovyvary	0.78	<0.01	-
g_p_ustinadlabem	0.37	<0.01	-
g_p_liberec	0.80	0.28	<0.01
g_p_hradeckralove	0.86	<0.01	-
g_p_pardubice	0.56	0.31	<0.01
g_p_jihlava	0.45	<0.01	-
g_p_brno	0.01	-	-
g_p_olomouc	0.96	<0.01	-
g_p_ostrava	<0.01	-	-
g_p_zlin	0.78	0.02	-
g_brigada	0.22	<0.01	-
g_volnamista	0.55	<0.01	-
g_nabidkaprace	0.84	<0.01	-
g_volnapracovnimista	0.83	<0.01	-
s_p	<0.01	-	-
s_p_praha	0.78	<0.01	-
s_p_ceskebudejovice	0.91	<0.01	-
s_p_plzen	0.89	<0.01	-
s_p_karlovyvary	0.01	-	-
s_p_ustinadlabem	0.17	<0.01	-
s_p_liberec	<0.01	-	-
s_p_hradeckralove	0.09	<0.01	-
s_p_pardubice	0.03	<0.01	-
s_p_jihlava	0.18	<0.01	-
s_p_brno	0.64	<0.01	-
s_p_olomouc	0.42	<0.01	-
s_p_ostrava	0.97	<0.01	-
s_p_zlin	<0.01	-	-
s_brigada	<0.01	-	-
s_volnamista	<0.01	-	-
s_nabidkaprace	<0.01	-	-
s_volnapracovnimista	<0.01	-	-
s_sum	<0.01	-	-

Table 6.2: Principal component analysis: Proportion of variance (Google data)

Component	**Eigenvalue**	**Proportion**	**Cumulative**
1	6.7434	0.3746	0.3746
2	4.9067	0.2726	0.6472
3	1.3938	0.0774	0.7247
4	0.8692	0.0483	0.7729
5	0.7161	0.0398	0.8127
6	0.6796	0.0378	0.8505
7	0.5009	0.0278	0.8783
8	0.4906	0.0273	0.9056
9	0.4376	0.0243	0.9299
10	0.3605	0.0200	0.9499
11	0.2532	0.0141	0.9640
12	0.1764	0.0098	0.9738
13	0.1339	0.0074	0.9812
14	0.1135	0.0063	0.9875
15	0.0718	0.0040	0.9915
16	0.0675	0.0037	0.9953
17	0.0564	0.0031	0.9984
18	0.0290	0.0016	1.0000

Table 6.3: Principal component analysis: Proportion of variance (Seznam data)

Component	**Eigenvalue**	**Proportion**	**Cumulative**
1	9.1995	0.5111	0.5111
2	3.3321	0.1851	0.6962
3	1.7941	0.0997	0.7959
4	0.8357	0.0464	0.8423
5	0.6308	0.0350	0.8773
6	0.5658	0.0314	0.9088
7	0.4327	0.0240	0.9328
8	0.2635	0.0146	0.9475
9	0.1944	0.0108	0.9582
10	0.1761	0.0098	0.9680
11	0.1552	0.0086	0.9767
12	0.1126	0.0063	0.9829
13	0.0879	0.0049	0.9878
14	0.0763	0.0042	0.9920
15	0.0659	0.0037	0.9957
16	0.0396	0.0022	0.9979
17	0.0224	0.0012	0.9991
18	0.0155	0.0009	1.0000

Table 6.4: In-sample performance of models incorporating individual variables

	$\bar{R}^2$	Δ	**RMSE**	Δ	**MAE**	Δ
(baseline)	0.006		0.130		0.094	
g_p	0.012	97%	0.131	0.5%	0.094	0.7%
g_p_praha	-0.012	-294%	0.132	1.6%	0.099	5.4%
g_p_ceskebudejovice	-0.009	-248%	0.132	1.7%	0.099	5.5%
g_p_plzen	-0.013	-319%	0.132	1.8%	0.099	5.3%
g_p_karlovyvary	-0.011	-286%	0.132	1.6%	0.098	4.7%
g_p_ustinadlabem	0.024	309%	0.132	1.6%	0.095	1.2%
g_p_liberec	-0.015	-348%	0.132	1.8%	0.098	4.6%
g_p_hradeckralove	0.002	-74%	0.131	1.0%	0.095	1.8%
g_p_pardubice	-0.013	-317%	0.132	1.8%	0.098	4.7%
g_p_jihlava	-0.011	-279%	0.133	2.2%	0.098	5.0%
g_p_brno	-0.002	-136%	0.131	0.8%	0.095	1.2%
g_p_olomouc	-0.011	-293%	0.132	1.6%	0.098	4.4%
g_p_ostrava	0.048	712%	0.128	-1.1%	0.093	-0.3%
g_p_zlin	-0.009	-256%	0.131	1.2%	0.098	4.6%
g_brigada	-0.015	-350%	0.132	1.7%	0.098	4.3%
g_volnamista	0.003	-53%	0.132	1.4%	0.095	1.8%
g_volnapracovnimista	0.030	398%	0.130	0.3%	0.102	9.0%
g_nabidkaprace	0.084	1308%	0.130	-0.1%	0.092	-1.7%
s_p	-0.009	-257%	0.132	2.0%	0.098	4.3%
s_p_praha	-0.001	-124%	0.131	1.0%	0.096	2.9%
s_p_ceskebudejovice	0.025	316%	0.133	2.4%	0.099	6.1%
s_p_plzen	-0.005	-177%	0.132	2.0%	0.098	4.8%
s_p_karlovyvary	-0.015	-360%	0.132	1.8%	0.098	4.5%
s_p_ustinadlabem	-0.004	-164%	0.132	1.9%	0.098	4.5%
s_p_liberec	0.028	364%	0.132	1.7%	0.098	4.5%
s_p_hradeckralove	-0.004	-161%	0.132	1.8%	0.098	4.2%
s_p_pardubice	-0.004	-164%	0.133	2.1%	0.098	4.3%
s_p_jihlava	0.031	422%	0.131	0.9%	0.097	3.3%
s_p_brno	-0.001	-109%	0.132	1.8%	0.098	4.4%
s_p_olomouc	0.007	25%	0.132	1.7%	0.097	3.8%
s_p_ostrava	-0.013	-326%	0.133	2.1%	0.098	4.4%
s_p_zlin	-0.015	-353%	0.132	1.8%	0.098	4.5%
s_brigada	-0.010	-265%	0.132	1.9%	0.098	4.3%
s_volnamista	-0.014	-333%	0.132	1.9%	0.099	5.3%
s_volnapracovnimista	-0.015	-345%	0.132	1.8%	0.098	4.5%
s_nabidkaprace	-0.015	-361%	0.132	1.8%	0.098	4.6%

Table 6.5: Out-of-sample performance of models incorporating indiviual variables

	RMSE	**Δ**	**MAE**	**Δ**
(baseline)	0.106		0.091	
g_p	0.117	10%	0.097	6%
g_p_praha	0.119	13%	0.099	9%
g_p_ceskebudejovice	0.120	13%	0.098	8%
g_p_plzen	0.119	12%	0.098	8%
g_p_karlovyvary	0.119	12%	0.098	8%
g_p_ustinadlabem	0.121	14%	0.101	11%
g_p_liberec	0.118	11%	0.096	6%
g_p_hradeckralove	0.117	10%	0.099	9%
g_p_pardubice	0.119	12%	0.098	8%
g_p_jihlava	0.127	19%	0.108	19%
g_p_brno	0.118	11%	0.097	7%
g_p_olomouc	0.118	12%	0.098	8%
g_p_ostrava	0.119	13%	0.100	10%
g_p_zlin	0.116	10%	0.096	6%
g_brigada	0.117	10%	0.098	8%
g_volnamista	0.119	13%	0.100	10%
g_volnapracovnimista	0.119	12%	0.098	8%
g_nabidkaprace	0.119	12%	0.098	8%
s_p	0.119	12%	0.098	8%
s_p_praha	0.116	9%	0.095	5%
s_p_ceskebudejovice	0.129	22%	0.109	20%
s_p_plzen	0.117	10%	0.096	6%
s_p_karlovyvary	0.119	12%	0.098	8%
s_p_ustinadlabem	0.122	15%	0.102	12%
s_p_liberec	0.119	13%	0.102	12%
s_p_hradeckralove	0.120	13%	0.099	9%
s_p_pardubice	0.119	12%	0.098	8%
s_p_jihlava	0.119	12%	0.097	6%
s_p_brno	0.119	12%	0.099	8%
s_p_olomouc	0.120	13%	0.101	11%
s_p_ostrava	0.119	12%	0.097	7%
s_p_zlin	0.119	12%	0.098	8%
s_brigada	0.119	12%	0.098	8%
s_volnamista	0.117	11%	0.098	8%
s_volnapracovnimista	0.119	12%	0.098	8%
s_nabidkaprace	0.119	12%	0.098	8%

Table 6.6: In-sample performance of models incorporating multiple or aggregate variables

	$\bar{R}^2$	Δ	**RMSE**	Δ	**MAE**	Δ
(baseline)	0.006		0.130		0.094	
G ALL	0.299	4946%	0.099	-24%	0.074	-21%
S ALL	0.359	5950%	0.101	-23%	0.085	-9%
s sum	-0.012	-305%	0.132	2%	0.098	4%
gPC (1)	0.005	-9%	0.132	1%	0.096	3%
gPC (2)	0.131	2115%	0.126	-3%	0.087	-7%
gPC (3)	0.115	1836%	0.126	-3%	0.087	-8%
gPC (4)	0.099	1564%	0.126	-3%	0.086	-8%
gPC (5)	0.079	1236%	0.126	-3%	0.086	-8%
gPC (6)	0.109	1732%	0.122	-6%	0.086	-8%
gPC (7)	0.091	1432%	0.122	-6%	0.086	-8%
gPC (8)	0.072	1105%	0.122	-6%	0.086	-8%
gPC (9)	0.063	965%	0.121	-7%	0.086	-8%
gPC (10)	0.044	644%	0.122	-6%	0.087	-7%
gPC (11)	0.060	912%	0.120	-7%	0.088	-6%
gPC (12)	0.115	1840%	0.116	-11%	0.085	-9%
gPC (13)	0.154	2499%	0.112	-14%	0.083	-11%
gPC (14)	0.167	2710%	0.109	-16%	0.081	-13%
gPC (15)	0.156	2536%	0.108	-17%	0.081	-13%
gPC (16)	0.267	4391%	0.102	-21%	0.076	-19%
gPC (17)	0.251	4124%	0.103	-20%	0.076	-19%
gPC (18)	0.271	4467%	0.101	-22%	0.076	-19%
sPC (1)	0.013	120%	0.133	2%	0.097	4%
sPC (2)	-0.005	-186%	0.133	2%	0.097	3%
sPC (3)	0.008	31%	0.130	0%	0.097	4%
sPC (4)	-0.014	-337%	0.130	0%	0.097	4%
sPC (5)	-0.033	-648%	0.131	1%	0.097	4%
sPC (6)	-0.055	-1025%	0.131	1%	0.096	2%
sPC (7)	-0.054	-1011%	0.132	1%	0.099	5%
sPC (8)	0.017	182%	0.132	2%	0.101	8%
sPC (9)	0.018	196%	0.131	1%	0.100	6%
sPC (10)	0.007	11%	0.130	0%	0.100	7%
sPC (11)	-0.019	-418%	0.133	2%	0.097	4%
sPC (12)	-0.046	-882%	0.133	2%	0.097	4%
sPC (13)	-0.066	-1219%	0.133	2%	0.097	4%
sPC (14)	-0.078	-1412%	0.133	2%	0.097	4%
sPC (15)	-0.042	-801%	0.133	2%	0.097	4%
sPC (16)	0.015	155%	0.133	2%	0.097	4%
sPC (17)	0.233	3823%	0.133	2%	0.097	4%
sPC (18)	0.320	5292%	0.133	2%	0.097	4%

Table 6.7: Out-of-sample performance of models incorporating multiple or aggregate variables

	RMSE	Δ	MAE	Δ
(baseline)	0.106		0.091	
G ALL	0.151	42%	0.129	42%
S ALL	0.431	306%	0.315	247%
s sum	0.119	12%	0.098	8%
gPC (1)	0.118	12%	0.099	9%
gPC (2)	0.117	10%	0.100	10%
gPC (3)	0.118	11%	0.101	11%
gPC (4)	0.118	11%	0.101	11%
gPC (5)	0.118	11%	0.101	11%
gPC (6)	0.117	10%	0.099	9%
gPC (7)	0.117	11%	0.100	10%
gPC (8)	0.117	10%	0.101	11%
gPC (9)	0.116	9%	0.099	9%
gPC (10)	0.115	8%	0.098	7%
gPC (11)	0.119	12%	0.102	12%
gPC (12)	0.121	14%	0.104	14%
gPC (13)	0.127	20%	0.109	20%
gPC (14)	0.124	17%	0.107	17%
gPC (15)	0.131	24%	0.114	25%
gPC (16)	0.156	47%	0.133	47%
gPC (17)	0.154	45%	0.132	45%
gPC (18)	0.153	44%	0.129	41%
sPC (1)	0.121	14%	0.100	10%
sPC (2)	0.121	14%	0.101	11%
sPC (3)	0.114	7%	0.097	7%
sPC (4)	0.114	7%	0.098	7%
sPC (5)	0.111	5%	0.094	3%
sPC (6)	0.112	6%	0.093	3%
sPC (7)	0.123	16%	0.101	11%
sPC (8)	0.166	57%	0.140	54%
sPC (9)	0.156	47%	0.135	48%
sPC (10)	0.166	56%	0.144	58%
sPC (11)	0.165	55%	0.143	58%
sPC (12)	0.165	55%	0.143	58%
sPC (13)	0.158	49%	0.138	52%
sPC (14)	0.170	60%	0.137	51%
sPC (15)	0.215	103%	0.154	69%
sPC (16)	0.258	144%	0.181	99%
sPC (17)	0.359	239%	0.241	165%
sPC (18)	0.432	307%	0.313	244%

Table 6.8: In-sample performance of models incorporating job search portal data

	$\bar{R}^2$	Δ	**RMSE**	Δ	**MAE**	Δ
(baseline)	0.006		0.130		0.094	
JV	0.050	749%	0.127	-2.3%	0.096	2.3%
JV(1)	0.024	308%	0.127	-2.1%	0.096	2.8%
JV(2)	0.021	253%	0.125	-3.4%	0.094	0.0%
JV(3)	0.104	1651%	0.122	-6.4%	0.088	-5.5%
JV(4)	0.087	1372%	0.121	-6.5%	0.088	-6.4%
JV(5)	0.071	1095%	0.121	-7.0%	0.086	-7.9%
JV(6)	0.049	730%	0.121	-7.0%	0.086	-7.9%
JV(7)	0.044	641%	0.120	-7.3%	0.085	-9.7%
JV(8)	0.049	730%	0.120	-8.0%	0.083	-11.3%
JV(9)	0.032	444%	0.119	-8.2%	0.083	-11.5%
JV(10)	0.015	159%	0.119	-8.6%	0.081	-13.2%
JV(11)	0.002	-65%	0.118	-9.4%	0.080	-14.4%
JV(12)	-0.026	-535%	0.118	-9.3%	0.080	-14.3%
JR	-0.012	-303%	0.132	1.7%	0.097	3.5%

Table 6.9: Out-of-sample performance of models incorporating job search portal data

	RMSE	Δ	**MAE**	Δ
(baseline)	0.106		0.091	
JV	0.104	-1.5%	0.085	-6.1%
JV(1)	0.104	-2.2%	0.085	-6.8%
JV(2)	0.104	-2.2%	0.084	-7.6%
JV(3)	0.108	1.8%	0.088	-2.9%
JV(4)	0.108	2.3%	0.089	-2.2%
JV(5)	0.109	2.6%	0.089	-1.8%
JV(6)	0.109	2.6%	0.089	-1.9%
JV(7)	0.111	4.7%	0.092	0.8%
JV(8)	0.111	4.2%	0.091	0.5%
JV(9)	0.110	3.9%	0.091	0.1%
JV(10)	0.111	4.8%	0.092	1.2%
JV(11)	0.109	3.1%	0.090	-0.9%
JV(12)	0.109	3.1%	0.090	-0.9%
JR	0.120	13.0%	0.099	8.9%

Table 6.10: DM test results

	JV	**JV(1)**	**JV(2)**	**JV(3)**	**JV(4)**	**JV(5)**	**JV(6)**	**JV(11)**	**JV(12)**
DM stat	-1.53	-1.64	-1.51	-0.60	-0.44	-0.37	-0.39	-0.20	-0.21
p-value	0.25	0.21	0.25	0.67	0.73	0.74	0.74	0.78	0.78

Chapter 7

Discussion

Irrespective of the results, the selected approach has some limitations and drawbacks that have to be taken into account. Some issues are common to all Google Econometrics studies while others are specific to this thesis.

In general, one of the main limitations of variables that are based on job-search related data from search engines is that they do not cover only searches made by unemployed people. As D'Amuri (2009) noted, part of the searches is driven by working people that e.g. intend to switch a job.This is important mostly because unemployed job search is believed to be anti-cyclical, the on the job search should be cyclical. Nevertheless, impact of this problem is difficult to estimate since there is little information on the number of working people looking for a new job.

Another issue is that job seekers that use the internet for their search activities might not be randomly selected. Search engines might be expected to be utilized more by young and/or educated people. This has been partially addressed by Fondeur & Karamé (2013) who focused solely on youth unemployment.

It is also important to note that the predictive ability of search query data may vary over time (Suhoy 2009). This has been confirmed e.g. by Choi & Varian (2012), who report substantial decrease of performance of Google variables after the recession.

As mentioned earlier, another limitation is caused by the sampling procedure used by Google to measure volumes of searches. This generates additional noise which is difficult to treat with the limited possibilities of data downloading on the Google Trends website.

As for the issues specific for this thesis, the limited length of the time-period has to be considered. The earliest month when data from all sources are available is February 2010, that means 61 observations until February 2015. Thus, principal component analysis as well as estimation and nowcasting results are somewhat less reliable.

Some bias might be also present in the Seznam data because of the changes in Seznam's search application. For details, see Section 5 (Methodology).

Chapter 8

Conclusion

In this thesis, we wanted to examine the usefulness of job search related web-based data for predictions of unemployment rate in the Czech Republic. We focused specifically on a comparison of performance of models augmented with search query data from Google and Seznam, two most popular search engines in the Czech Republic. We compared them in two ways—first, we inspected the contribution of each single added search query variable to the in-sample fit and out-of-sample forecast accuracy. Second, we compared models augmented with multiple or aggregated search query variables. Apart from this comparison of contributions of different search engines, we examined the usability of data on numbers of job vacancies and answers to them, obtained from a Czech job search portal Jobs.cz. In total, we estimated and compared 91 different models.

Adding individual search query variables mostly worsens both in-sample and out-of-sample performance compared to the baseline model for both Google and Seznam data. Out of 18 models with Google variables, only five outperformed the baseline model in terms of $\bar{R}^2$. Out of the same number of models using Seznam variables, only four had higher $\bar{R}^2$ than the baseline model. Regarding out-of-sample performance, none of the variables improved the nowcasts after adding to the model. The MAE increased in all cases, with the differences ranging from 6 to 20 %.

Comparison of models that are attempting to incorporate all information gathered from each search engine brings more interesting results. Models using all 18 variables at once show great improvements of in-sample fit, up to 0.30 for a model with Google data and 0.36 for a model with Seznam data. We also utilized principal component analysis to aggregate the information from Google and Seznam data. In terms of in-sample performance, Google PCs explain the unemployment rate somewhat better. A model incorporating first two Google PCs reaches $\bar{R}^2$ of 0.131. Nevertheless, none of the models improves the out-of-sample nowcast accuracy—the MAE increases by 7 to more than 240 %. In general, we found that none of the models augmented with any Google or Seznam variables helps improve the nowcasts and we cannot hence effectively distinguish which one improves the predictions more.

The last area of our interest was the usefulness of data on job vacancies and answers to them obtained from Jobs.cz. Here we find the most consistent improvements of fit, including improvement of out-of-sample performance. This however holds only for number of job vacancies, the reactions worsened both in-sample and out-of-sample performance, when added to the baseline model. As for the models that include the job vacancies variable, the $\bar{R}^2$ reaches up to 0.104. What is more important is the nowcasting performance—9 models increase the accuracy in terms of MAE. The greatest improvement is a 7.6% decrease in MAE. Nevertheless, none of the forecasts improvement turns out to be statistically significant, according to the Diebold-Mariano (DM) test.

All in all, our results do not look very compelling. We were not able to find any improvements of unemployment rate predictions after adding Google or Seznam data. This might be caused by the variability of predictive ability of web search data over time or by the shorter time period which does not allow to build reliable enough models. Further issues are discussed in the previous chapter. On the other hand, we achieved good results with the models augmented with job vacancies data. This is especially interesting given the comparison with search query data performance and also the fact that the job search portal used focuses only on a small subset of the labour market.

Our research could be enhanced in two possible ways. First, given the Czech Republic data, it would be useful to reestimate the models later when more information is collected and/or utilize some more sophisticated models. Second, a similar research using data on job vacancies as a dependent variable in other countries or involving a more widely oriented job search portal would be interesting to confirm or reject their usefulness for explaining unemployment rate.

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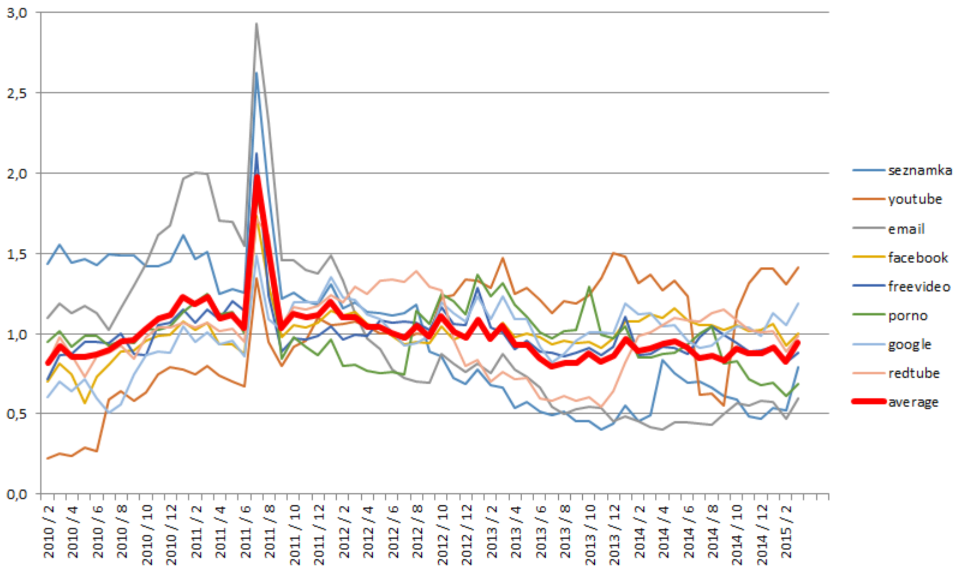
Appendix A

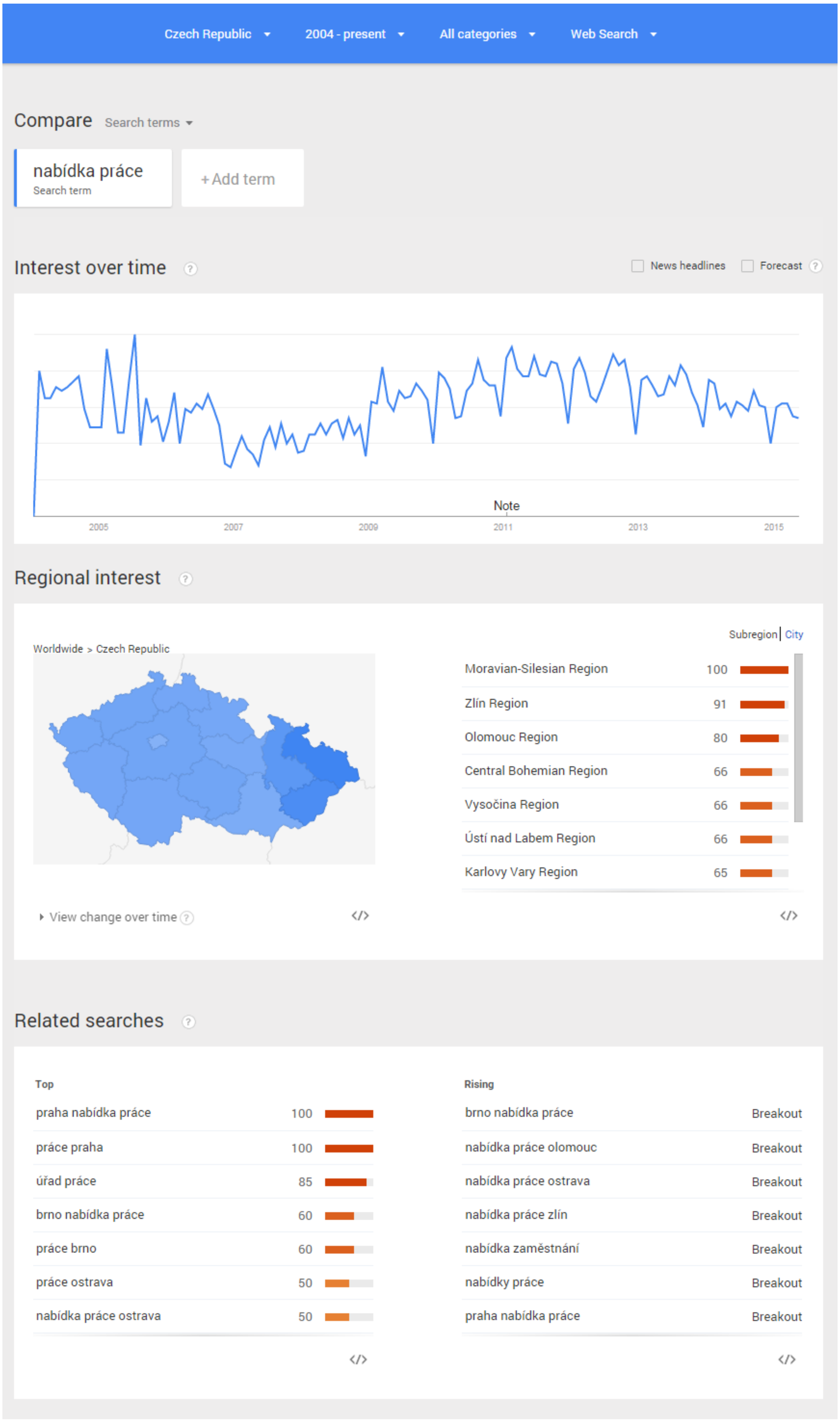
Additional figures

Figure A.1: Development of search volumes of "neutral" queries (rescaled)



Note: each series normalized by its mean for easier comparison

Figure A.2: Google Trends website



Czech Republic ▾ 2004 - present ▾ All categories ▾ Web Search ▾

Compare Search terms ▾

nabídka práce
Search term

+ Add term

Interest over time ?

□ News headlines □ Forecast ?

Regional interest ?

Worldwide > Czech Republic

Subregion | City

Moravian-Silesian Region	100	
Zlín Region	91	
Olomouc Region	80	
Central Bohemian Region	66	
Vysočina Region	66	
Ústí nad Labem Region	66	
Karlovy Vary Region	65	

▸ View change over time ?

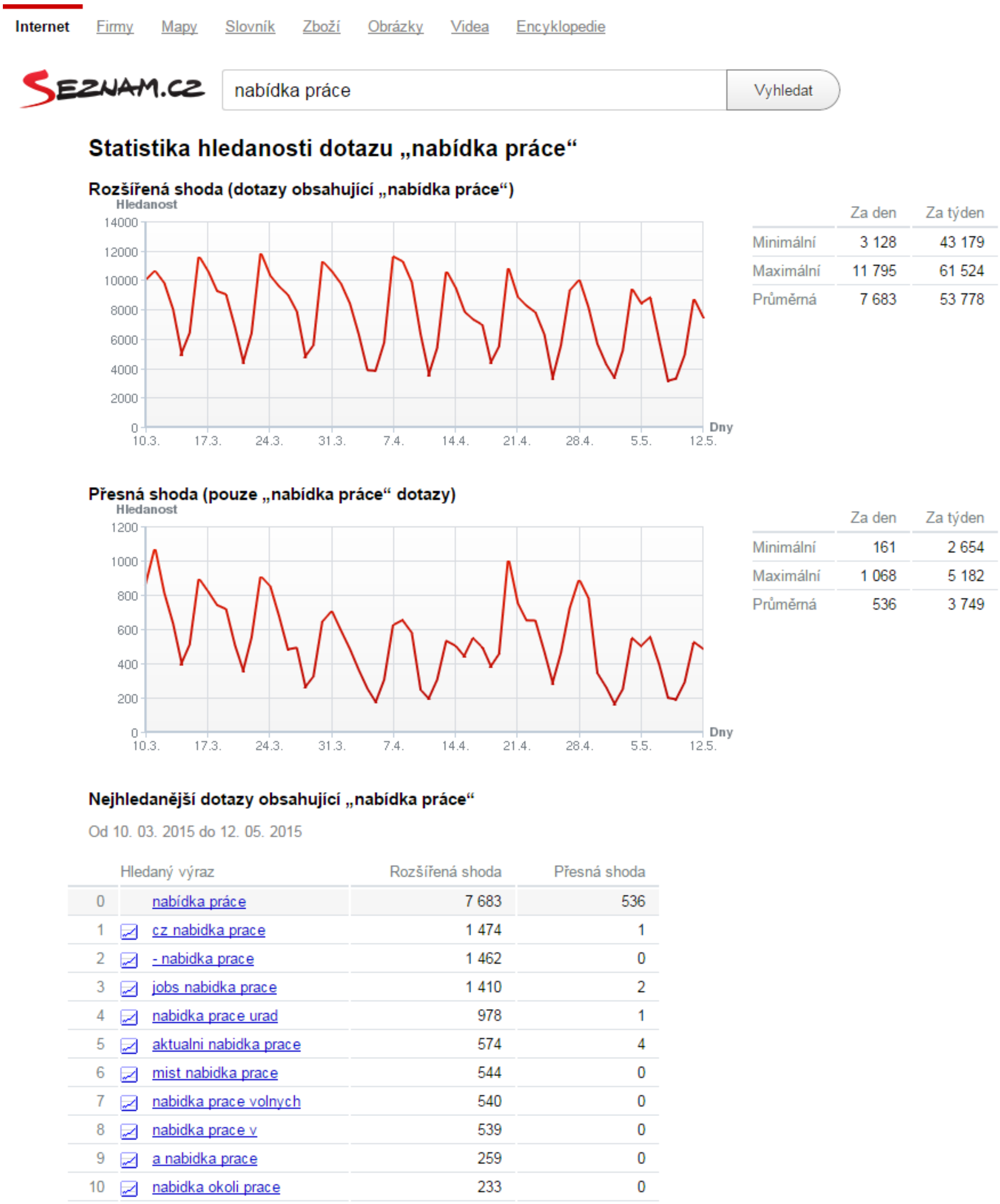
Related searches ?

Top	
praha nabídka práce	100
práce praha	100
úřad práce	85
brno nabídka práce	60
práce brno	60
práce ostrava	50
nabídka práce ostrava	50

Rising	
brno nabídka práce	Breakout
nabídka práce olomouc	Breakout
nabídka práce ostrava	Breakout
nabídka práce zlín	Breakout
nabídka zaměstnání	Breakout
nabídky práce	Breakout
praha nabídka práce	Breakout

Source: http://www.google.com/trends

Figure A.3: Seznam.cz search statistics website



Statistika hledanosti dotazu „nabídka práce“

Rozšířená shoda (dotazy obsahující „nabídka práce“)

	Za den	Za týden
Minimální	3 128	43 179
Maximální	11 795	61 524
Průměrná	7 683	53 778

Přesná shoda (pouze „nabídka práce“ dotazy)

	Za den	Za týden
Minimální	161	2 654
Maximální	1 068	5 182
Průměrná	536	3 749

Nejhledanější dotazy obsahující „nabídka práce“

Od 10. 03. 2015 do 12. 05. 2015

	Hledaný výraz	Rozšířená shoda	Přesná shoda
0	nabídka práce	7 683	536
1	cz nabidka prace	1 474	1
2	- nabidka prace	1 462	0
3	jobs nabidka prace	1 410	2
4	nabidka prace urad	978	1
5	aktualni nabidka prace	574	4
6	mist nabidka prace	544	0
7	nabidka prace volnych	540	0
8	nabidka prace v	539	0
9	a nabidka prace	259	0
10	nabidka okoli prace	233	0

Source: http://search.seznam.cz/stats

Appendix B

Additional tables

Table B.1: Percentage of households with Internet access in the Czech Republic and EU15

	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
	Households living in densely-populated area (at least 500 inhabitants/km^2*)*						
EU15	67	72	76	78	80	84	85
Czech Republic	53	61	63	69	68	77	85
	Households living in intermediate urbanized area (between 100 and 499 inhabitants/km^2*)*						
EU15	64	69	73	75	77	81	84
Czech Republic	44	52	61	67	65	73	77
	Households living in sparsely populated area (less than 100 inhabitants/km^2*)*						
EU15	59	64	67	71	73	78	79
Czech Republic	41	50	58	64	63	69	74

Source: Eurostat (2015a)

Table B.2: Survey results: Frequencies of most used search queries

Search Query	Freq	Search Query	Freq
Prace	34	zkraceny uvazek	3
prace praha	17	nabidky prace praha	3
brigada	16	prace ceske budejovice	3
Praha	14	prace v cb	2
administrativa	14	pracovni prilezitosti	2
volna pracovni mista	14	prace z domova	2
volna mista	14	delnice	2
Hledam praci	14	prace na hpp	2
nabidka prace	13	fajn-brigady.cz	2
brigada praha	9	prace v Jihlave	2
brigady	7	hledam	2
asistentka	6	pracovni nabidky praha	2
prace zlin	6	HPP	2
volne pracovni pozice	6	volna pracovni mista ceske Budejovice	2
prace v praze	6	jobs	2
hosteska	5	prace pro studenty	2
zamestnani	5	nabidka prace	2
brigada pro studenty	4	prace v ceskych budejovicich	2
urad prace	4	Bar	2
brigady praha	4	prace vysocina	2
prace.cz	4	ponuka prace	2
nabidky prace	4	pracovni nabidky	2
obchod	3	pozice	2
kuchar	3	pracovni portal	2
brigada zlin	3	prace cb	2
Prace	3	brigada Plzen	2
volna pozice	3	prace jihlava	2
prodavacka	3	volne pracovni mista	2
hlidani deti	3	Prace Jihlava	2
recepcni	3	...	2

Table B.3: Principal component loadings

Google data

	gPC1	gPC2	gPC3	gPC4	gPC5	gPC6	gPC7	gPC8	gPC9	gPC10	gPC11	gPC12	gPC13	gPC14	gPC15	gPC16	gPC17	gPC18
g_p	0.346	0.149	0.007	0.160	0.174	0.030	0.081	-0.006	0.158	0.112	-0.022	-0.015	-0.018	-0.002	0.058	0.066	-0.016	0.865
g_p_praha	0.355	0.035	0.096	0.192	0.092	0.002	0.158	0.169	-0.120	-0.043	-0.101	-0.305	-0.020	0.201	-0.011	0.703	-0.216	-0.253
g_p_ceskebudejovice	0.045	-0.397	-0.008	0.129	-0.059	0.014	0.080	-0.267	-0.377	-0.275	-0.095	0.527	0.178	-0.110	0.343	0.249	0.062	0.103
g_p_plzen	0.189	-0.137	-0.429	-0.381	-0.224	0.048	0.575	0.338	-0.027	0.040	0.266	0.093	-0.062	0.109	0.100	-0.076	-0.067	0.019
g_p_liberec	0.203	-0.315	0.016	-0.366	0.159	0.191	-0.005	-0.122	0.180	-0.035	-0.104	-0.015	0.408	0.038	-0.531	0.137	0.368	0.011
g_p_hradeckralove	0.098	-0.265	-0.204	0.308	-0.685	-0.190	-0.168	0.021	0.271	0.244	-0.265	0.022	-0.074	0.072	-0.132	0.080	0.105	0.027
g_p_pardubice	0.209	-0.341	-0.002	-0.139	0.059	0.025	-0.128	0.027	0.101	-0.122	0.062	-0.298	-0.437	-0.677	0.136	0.057	0.099	-0.028
g_p_brno	0.317	0.226	-0.008	0.058	0.063	0.025	-0.039	-0.041	0.160	0.112	0.066	-0.012	0.053	0.169	0.510	-0.060	0.663	-0.245
g_p_olomouc	0.063	-0.309	0.400	-0.004	0.063	-0.325	0.165	-0.251	-0.252	0.511	0.352	-0.024	-0.209	0.159	-0.115	-0.053	0.080	0.004
g_p_ostrava	0.347	0.042	0.006	0.104	0.093	0.145	-0.188	-0.011	0.096	-0.295	0.157	0.461	-0.527	0.261	-0.311	-0.102	-0.035	-0.121
g_p_zlin	0.144	-0.374	-0.004	-0.170	0.083	0.173	-0.116	-0.252	0.083	-0.059	-0.301	-0.295	-0.048	0.439	0.321	-0.317	-0.332	0.001
g_brigada	0.319	-0.016	0.117	0.362	0.127	-0.080	0.388	0.154	-0.151	-0.015	-0.395	0.007	0.129	-0.239	-0.170	-0.493	-0.005	-0.180
g_volnamista	-0.142	-0.161	-0.497	0.223	0.534	-0.240	0.088	-0.163	0.378	0.225	0.016	0.162	0.010	-0.052	0.022	0.102	-0.135	-0.167
g_volnapracovnimista	-0.155	-0.315	-0.032	0.277	0.112	-0.346	-0.073	0.343	-0.011	-0.486	0.281	-0.265	0.105	0.251	-0.027	-0.111	0.221	0.148
g_nabidkaprace	0.334	-0.072	0.049	0.184	-0.112	0.160	-0.282	0.038	0.110	0.101	0.532	0.032	0.480	-0.170	0.063	-0.128	-0.356	-0.122
g_p_jihlava	0.153	0.267	-0.330	0.060	-0.186	-0.173	0.152	-0.660	-0.148	-0.293	0.178	-0.310	0.019	-0.041	-0.169	-0.055	0.012	-0.011
g_p_ustinadlabem	0.233	0.066	-0.404	-0.190	0.153	-0.249	-0.492	0.190	-0.555	0.207	-0.136	-0.001	0.033	0.015	-0.062	-0.054	0.018	0.039
g_p_karlovyvary	0.206	0.142	0.261	-0.391	-0.052	-0.682	-0.027	0.004	0.299	-0.206	-0.118	0.192	0.119	-0.047	0.104	0.025	-0.191	-0.038

Seznam data

	sPC1	sPC2	sPC3	sPC4	sPC5	sPC6	sPC7	sPC8	sPC9	sPC10	sPC11	sPC12	sPC13	sPC14	sPC15	sPC16	sPC17	sPC18
s_p	0.260	0.298	-0.026	-0.032	-0.021	0.050	0.077	-0.225	-0.052	0.415	0.332	-0.111	0.010	0.167	0.126	-0.299	-0.562	0.190
s_p_praha	0.071	-0.433	-0.298	-0.034	0.032	-0.457	0.104	-0.359	-0.106	0.103	0.023	-0.040	0.026	0.063	-0.185	-0.070	-0.125	-0.534
s_p_ceskebudejovice	0.278	-0.147	-0.012	-0.243	0.163	-0.094	-0.411	0.254	-0.160	-0.167	0.085	0.371	-0.529	0.229	0.146	-0.099	-0.102	-0.020
s_p_plzen	-0.038	-0.449	0.271	0.032	0.032	0.059	0.374	0.520	0.288	0.368	0.124	0.011	-0.046	0.217	-0.110	-0.105	-0.019	-0.022
s_p_karlovyvary	0.271	-0.034	-0.146	-0.168	-0.467	-0.004	0.234	0.235	0.066	-0.616	0.181	-0.093	0.258	0.123	-0.020	-0.108	-0.167	-0.011
s_p_ustinadlabem	0.281	0.058	0.017	-0.183	0.387	-0.263	-0.226	0.340	-0.224	0.123	-0.023	-0.153	0.575	0.045	-0.128	0.226	-0.000	0.095
s_p_liberec	0.189	0.075	0.041	0.776	-0.328	-0.261	-0.088	0.223	-0.308	0.085	-0.059	0.009	-0.056	0.083	0.055	0.020	0.042	-0.022
s_p_hradeckralove	0.293	0.059	0.099	0.161	0.175	-0.146	-0.192	-0.110	0.548	-0.169	-0.291	-0.460	-0.211	0.171	-0.229	-0.120	-0.016	0.087
s_p_pardubice	0.310	-0.030	0.105	-0.014	-0.014	0.142	0.092	-0.113	-0.111	0.045	-0.400	0.435	0.193	-0.152	-0.342	-0.531	0.118	0.113
s_p_jihlava	0.307	-0.054	0.153	-0.088	0.017	0.192	0.025	0.054	-0.026	0.082	-0.230	-0.270	0.068	-0.193	0.659	-0.179	0.136	-0.414
s_p_brno	0.289	-0.164	-0.136	-0.167	-0.205	-0.106	0.085	-0.255	-0.029	0.194	0.175	-0.084	-0.053	0.231	0.133	0.078	0.632	0.402
s_p_olomouc	0.176	-0.212	0.457	0.083	0.148	0.384	0.144	-0.275	-0.433	-0.217	0.071	-0.187	-0.084	0.205	-0.201	0.265	-0.079	-0.038
s_p_ostrava	0.137	-0.480	-0.090	0.050	-0.084	-0.036	0.006	-0.079	0.076	0.014	-0.281	0.059	-0.001	-0.360	0.214	0.313	-0.408	0.443
s_p_zlin	0.301	0.072	-0.113	-0.115	-0.190	0.165	-0.082	0.180	-0.033	0.198	0.240	-0.202	-0.297	-0.581	-0.410	0.134	0.069	-0.143
s_brigada	0.195	0.368	-0.151	-0.178	-0.086	0.003	0.397	0.066	0.025	0.158	-0.453	0.176	-0.184	0.265	-0.040	0.450	-0.082	-0.162
s_volnamista	0.178	0.051	-0.403	0.315	0.590	0.072	0.436	0.069	0.001	-0.218	0.198	0.065	-0.100	-0.157	0.103	-0.053	0.101	0.084
s_nabidkaprace	0.296	0.005	0.116	0.206	-0.007	0.168	-0.206	-0.200	0.467	0.027	0.303	0.452	0.272	0.023	0.045	0.307	0.031	-0.247
s_volnapracovnimista	0.057	0.194	0.568	-0.124	0.041	-0.584	0.300	-0.091	0.039	-0.131	0.154	0.130	-0.118	-0.311	0.084	0.030	0.022	0.045

Table B.4: ADF test results for principal components: p-values

	Level	First difference	Second difference		Level	First difference	Second difference
gPC1	0.07	<0.01	-	**sPC1**	0.95	<0.01	-
gPC2	0.44	<0.01	-	**sPC2**	0.95	0.02	-
gPC3	0.89	<0.01	-	**sPC3**	0.57	0.22	<0.01
gPC4	0.02	-	-	**sPC4**	0.34	0.53	<0.01
gPC5	0.87	<0.01	-	**sPC5**	0.17	<0.01	-
gPC6	0.22	<0.01	-	**sPC6**	0.49	<0.01	-
gPC7	0.02	-	-	**sPC7**	0.05	<0.01	-
gPC8	0.02	-	-	**sPC8**	0.08	<0.01	-
gPC9	<0.01	<0.01	-	**sPC9**	0.03	-	-
gPC10	<0.01	<0.01	-	**sPC10**	<0.01	<0.01	-
gPC11	0.05	<0.01	-	**sPC11**	0.59	<0.01	-
gPC12	0.21	<0.01	-	**sPC12**	0.02	<0.01	-
gPC13	0.31	<0.01	-	**sPC13**	0.16	<0.01	-
gPC14	0.44	<0.01	-	**sPC14**	0.18	<0.01	-
gPC15	0.36	<0.01	-	**sPC15**	0.69	<0.01	-
gPC16	0.58	<0.01	-	**sPC16**	0.07	<0.01	-
gPC17	0.44	<0.01	-	**sPC17**	0.39	<0.01	-
gPC18	0.76	<0.01	-	**sPC18**	0.02	-	-

Table B.5: Descriptive statistics (1/2)

Variable	Mean	Median	Minimum	Maximum
unemp	6.85028	6.97991	5.84002	7.91285
j_vacancies	210.440	209.936	176.872	242.569
j_reactions	2319.15	3086.70	−1.00000	3405.24
g_p	60.3628	61.7766	48.7522	72.1430
g_p_praha	65.2626	65.9660	55.9525	74.2921
g_p_ceskebudejovice	39.7401	47.2491	−1.04559	61.6004
g_p_plzen	38.0938	38.4667	0.000000	66.3214
g_p_liberec	30.7449	31.0329	−1.23299	54.1764
g_p_hradeckralove	41.4406	42.9032	0.000000	81.3214
g_p_pardubice	38.8881	40.6000	0.000000	73.3571
g_p_brno	52.0304	51.0900	40.3039	63.2263
g_p_olomouc	42.8080	44.9699	8.80528	58.9778
g_p_ostrava	51.0336	51.1118	41.3799	60.4039
g_p_zlin	30.6161	33.2581	0.000000	52.7419
g_brigada	28.0181	28.2643	22.2645	31.6802
g_volnamista	54.3335	54.7955	45.7911	61.1486
g_volnapracovnimista	62.2120	63.3999	44.8913	76.6187
g_nabidkaprace	62.4737	62.5325	51.3125	87.8907
g_p_jihlava	60.4262	58.0000	34.0000	93.0000
g_p_ustinadlabem	52.7541	52.0000	22.0000	100.000
g_p_karlovyvary	58.5706	58.7577	35.1531	103.175
s_p	10328.2	10420.3	5164.74	20940.7
s_p_praha	617.328	457.659	244.572	1731.14
s_p_ceskebudejovice	192.512	201.959	41.4417	365.351
s_p_plzen	137.992	132.635	52.6780	267.676
s_p_karlovyvary	131.346	133.188	36.2974	225.194
s_p_ustinadlabem	109.965	114.392	37.5987	288.905
s_p_liberec	190.326	192.618	96.3990	291.058
s_p_hradeckralove	160.915	156.178	54.9328	393.968
s_p_pardubice	187.305	182.925	71.3495	394.289
s_p_jihlava	143.051	140.619	49.5621	318.669
s_p_brno	1078.52	1219.53	225.191	1906.65
s_p_olomouc	353.991	321.673	187.075	622.239
s_p_ostrava	392.459	273.394	157.500	739.710
s_p_zlin	194.125	198.207	128.018	250.964
s_brigada	541.696	467.620	151.136	1519.03
s_volnamista	868.197	894.823	310.683	1874.86
s_nabidkaprace	3280.93	3221.42	1764.23	5287.45
s_volnapracovnimista	2924.45	2925.80	640.351	4911.26
s sum	21833.3	22067.2	12382.8	40411.8

Note: −1 stands for missing observation

Table B.6: Descriptive statistics (2/2)

Variable	Std. Dev.	C.V.	Skewness	Ex. kurtosis
unemp	0.472890	0.0690322	−0.556015	−0.0325426
j_vacancies	14.8247	0.0704462	−0.0489082	−0.491904
j_reactions	1352.90	0.583358	−1.09964	−0.687382
g_p	6.93569	0.114900	−0.0998279	−1.40296
g_p_praha	4.53398	0.0694729	−0.353667	−0.798165
g_p_ceskebudejovice	20.4428	0.514412	−1.20413	−0.138357
g_p_plzen	13.4114	0.352063	−0.780380	1.86568
g_p_liberec	13.8745	0.451280	−0.839692	0.418079
g_p_hradeckralove	18.8312	0.454415	−0.704415	0.369456
g_p_pardubice	16.4067	0.421894	−0.694611	0.475624
g_p_brno	6.84913	0.131637	0.0460955	−1.32561
g_p_olomouc	11.4156	0.266671	−1.75889	2.69438
g_p_ostrava	4.80233	0.0941012	0.0288705	−0.916652
g_p_zlin	13.2924	0.434165	−1.13973	0.861815
g_brigada	1.93190	0.0689519	−0.333344	0.0938161
g_volnamista	3.59370	0.0661416	−0.136533	−0.747204
g_volnapracovnimista	7.89777	0.126949	−0.434232	−0.401579
g_nabidkaprace	6.87063	0.109976	0.941762	1.94015
g_p_jihlava	15.5515	0.257363	0.443523	−0.658802
g_p_ustinadlabem	12.4722	0.236421	0.826663	2.22767
g_p_karlovyvary	13.3120	0.227282	0.565036	1.01606
s_p	3358.07	0.325138	0.547029	0.0269732
s_p_praha	419.538	0.679603	1.32781	0.680995
s_p_ceskebudejovice	79.3838	0.412358	−0.198193	−0.573823
s_p_plzen	57.7852	0.418758	0.436280	−1.05103
s_p_karlovyvary	46.1276	0.351190	−0.381453	−0.471661
s_p_ustinadlabem	44.1411	0.401412	0.786064	3.03361
s_p_liberec	40.0336	0.210343	−0.220417	0.457407
s_p_hradeckralove	53.5252	0.332630	1.02561	4.91552
s_p_pardubice	63.1064	0.336917	0.445847	0.634455
s_p_jihlava	55.3501	0.386926	0.531645	0.557167
s_p_brno	416.446	0.386127	−0.721563	−0.530108
s_p_olomouc	114.152	0.322471	0.817815	−0.286259
s_p_ostrava	191.629	0.488278	0.436743	−1.51277
s_p_zlin	30.1161	0.155137	−0.717414	−0.103687
s_brigada	327.063	0.603775	0.714253	−0.322026
s_volnamista	302.903	0.348887	0.728654	1.10974
s_nabidkaprace	646.518	0.197053	0.262430	0.708066
s_volnapracovnimista	544.446	0.186170	−0.440376	6.43108
s sum	4979.04	0.228048	0.617270	1.97311